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MEASURING SOCIAL INTEGRATION: LINKING PERSONAL AND ASSOCIATIONAL TIES IN EGO NETWORKS

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by

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MEASURING SOCIAL INTEGRATION:

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Objective: Social integration is a foundational feature of society that influences individual-level outcomes. However, as our social worlds increase in complexity, integration becomes difficult to precisely measure. Contributing to research on social integration, this dissertation: (1) develops more precise ways to measure social integration, (2) identifies who is socially integrated, and (3) explores which social ties have the most influence on social integration.

Study 1: The first study aims to measure social integration more precisely by establishing a network structure and set of measures that utilize personal and associational ties with ego network data. Defined as personal affiliation networks (PAN), this study identifies 15 measures capturing unique aspects of PANs, bridging personal and associational ties.

Study 2: Pairing the methodological framework from Study 1 with the 2006 National Voluntary Association Study (NVAS), Study 2: (1) describes the distribution of, and the relationship between the PAN measures and (2) identifies ego-level characteristics associated with social integration in PANs. This study identifies that established differences in integration across demographic groups do not always hold when using more nuanced integration measures. Rather, I find that associational ties can supplement personal ties, washing out many group differences; concluding that

tie characteristics of alters may be more influential for individual integration than ego characteristics alone.

Study 3: Study 3 further explores the role that alters have on social integration, identifying: (1) who bridges the personal and associational spaces of individuals and (2) who has the most influence on individual social integration. This study shows that spouses and stronger ties have the highest influence on social integration. High integrating alters also share more social contexts with egos, specifically those that bridge personal and associational spaces have more influence on social integration overall.

Conclusion: This dissertation demonstrates the importance of incorporating personal and associational ties within the measurement of social integration. Higher precision in measures of social integration yield important benefits for understanding complexities of social connectivity and its consequences for individuals.

DEDICATION

To my strong, smart, and powerful child: Leena Rose Salvador.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

CHAPTER 1 INTRODUCTION

1.1 INTRODUCTION

The fabric of society is constituted by social interactions, and since its conception, sociology has aimed to understand the consequences that social connectivity has on individuals. Focusing on social interactions, theorists such as Durkheim, Simmel, and Tocqueville have tried to explain how social relations structure the social world and what influence this structure has on individuals (Almedom 2005; Berkman et al. 2000; Berkman and Glass 2000; Breiger 1974; Durkheim 1951; Feld 1981; Kawachi and Berkman 2001; Pescosolido and Georgianna 1989; Pescosolido and Rubin 2000; Simmel 1955; Tocqueville 2003). Social integration, defined as the ties that bind individuals to groups, has commonly been used as a tool to measure social influence. At its core, social integration is a product of social connections that directly influence individuals (Bearman 1991; Blau 1960).

Researchers have used personal (ego) networks and voluntary associations to measure individual social integration. Although their integrating contexts differ, with ego networks binding individuals to each other and voluntary associations binding individuals to groups, both have been associated with a host of individual outcomes, from health and psychological well-being to economic opportunity and political engagement (Berkman and Glass 2000; Blau 1960; Friedkin 2004; Marsden and Friedkin 1993; McCarty 2002; Perry and Pescosolido 2010; Simmel 1955; Smith and Christakis 2008).

Ego networks, which focus on the personal ties of individuals, are used to capture the composition and structure of an individual's (that is, an ego's) social environment (Perry, Pescosolido, and Borgatti 2018; Smith 2019). Actors in an ego network—often referred to as alters—are commonly operationalized as the individuals with whom egos share close ties. Measured as discussion partners, close confidants, or even co-drug users, these close ties constitute an ego's immediate social environment (De et al. 2007; Marsden 1987; Perry et al. 2018). Both compositional and structural features have been associated with individual-level outcomes. For example, previous studies have used simple structural measures of personal networks, such as size and density, as a proxy for social integration to predict how resources are mobilized, how information spreads, and how social support operates (Binder, Roberts, and Sutcliffe 2012; Campbell and Lee 1992; Marsden and Friedkin 1993; McCarty 2002; Pena-López and Sánchez-Santos 2017; Verdery and Campbell 2019).

While particularly useful for tying together individuals, ego networks usually fail to explore social connections beyond a personal level. Other types of ties, however, also contribute to individual social integration. For example, meso-level ties generated by voluntary associations (e.g., church groups, book clubs, sports groups) operate as important sources of connectivity, tying individuals to communities. Like personal social networks, organizations operate as sources of resource mobilization, increased social cohesion, and regulation of norms (e.g., political ideologies) (Babchuk and Edwards 1965; Bekkers 2005; Benton 2016; Bonikowski and McPherson 2007; Cornwell and Harrison 2004). Although voluntary associations can operate as integrating spaces, little research has been able to infuse personal network ties within this context.

Both ego network and voluntary association measures include information about the social ties integrating individuals: Ego networks measure the social ties that an individual has to people at the core of their immediate social environment (i.e., alters), and measures of voluntary association participation capture the ties that individuals have to groups. In typical studies, however, these two types of social ties are measured in isolation. In reality, however, individuals may share other types of social ties with the people they are most close with. Even ego network studies that happen to incorporate associational measures into their design, such as the General Social Survey, do not directly measure if (or how) alters share the same associational ties. The lack of detailed data about how alters may be tied to an ego's voluntary associations means that researchers miss important features of social life.

Because traditional ego network data does not capture the ties between alters and associations, few measures have been developed to account for these types of ties, and few researchers have attempted to empirically study the overlap between personal and associational ties in ego network data. Due to these methodological limitations, current research studying social integration can neither identify how social integration operates for different demographic groups (i.e., who is integrated?) nor identify which actors in a network contribute to individual social integration (i.e., who is integrating?). This dissertation works to overcome some of these limitations by (1) more precisely measuring social integration, (2) reexamining previous findings on the relationship between social integration and ego demographic correlates when using more precise measures of social integration, and (3) identifying which alters influence social integration, and to what extent they do so.

1.1.1 Specific Aims

To address existing research gaps directly, this dissertation aims to:

Aim 1: Establish a network structure that captures personal and associational ties simultaneously.

Aim 2: Construct a series of measures that more precisely capture social integration using the network structure identified in Aim 1.

Aim 3: Describe the distribution of, and the relationship between, measures of social integration using personal and associational ties.

Aim 4: Establish whether individual (ego) level sociodemographic characteristics are associated with the newly developed measures of social integration developed in Aim 2.

Aim 5: Establish the relative influence that actors in a network have on the social integration of individuals.

Aim 6: Test whether specific alter characteristics are associated with individual-level social integration.

By considering these six aims, this dissertation contributes to the empirical and theoretical literatures concerning individual social integration, complex social systems, and individual well-being.

1.2 SIGNIFICANCE AND INNOVATION

Social connections extend beyond personal ties alone, often to other contexts in an individual's social environment, including voluntary associations, work, and other sources of support. With social ties directly influencing social integration, changes in network structure, such as the loss of a tie, may have important consequences for individual outcomes. Current research, however, cannot identify the consequences of altering (whether reducing or removing) social connections on social integration beyond personal ties. For example, researchers are likely to need new, better measures of personal networks when exploring the consequences of the COVID-19 pandemic on integration. Even though this dissertation will not take on this case empirically, it is instructive to postulate how the measures I develop in this dissertation could be applied in this unprecedented, historical moment.

The COVID-19 pandemic has had a deleterious effect on social connectivity. The loss of social ties—be it to death, separation, restriction, or otherwise—has resulted in increased social isolation and loneliness (Kovacs et al. 2021; Krendl and Perry 2021; Peng and Roth 2021), exacerbated social inequalities (Abedi et al. 2021; Bowleg 2020; Elgar, Stefaniak, and Wohl 2020; Gauthier et al. 2021; Killgore et al. 2020; Patel et al. 2020), and amplified mental and physical health disparities (Ettman et al. 2020; Fitzpatrick, Harris, and Drawve 2020; Killgore et al. 2020; Krendl and Perry 2021; Kujawa et al. 2020; van Tilburg et al. 2020). The loss or change in social connections has a direct impact on individuals that extends beyond personal ties alone. For example, "sheltering in place" policies have altered not only personal ties but associational ties as well (Krendl and Perry 2021).

The reduction in associative habits coupled with the loss of personal ties has negative implications for individuals, reducing both personal and associational ties concurrently (Demir-Dagdas and Child 2019; Dutra and Rocha 2021; Krendl and Perry 2021). This concurrent loss of ties, for example, may be especially damning if an individual's personal and associational ties are highly overlapping: the reduction of a personal tie also results in a reduction of ties integrating an individual to an association.

While current studies utilize simple measures of social integration for either personal ties or associational ties, they often miss important aspects of social life—namely, how personal and associational ties exist concurrently and may overlap with each other. Furthermore, current measures cannot identify whether personal ties can be substituted by other types of ties, like associational ties. If an individual has few close personal ties but a large number of ties to associations, for example, current measures cannot identify whether those many weak ties to associations could offset the lack of strong ties to individuals. Additionally, current measures fail to account for whether named alters are also tied to the voluntary associations of which an ego is a member. Extending the previous example, current measures cannot identify the implications for dropping out of clubs if all of the named alters share memberships to the same associations. For example, dropping out of a club where many of one's friends are members might be particularly detrimental for social integration. Given the turbulent conditions of social connectivity, current measures cannot assess how the loss of a tie (let alone a highly embedded tie) may impact the larger network structure of an individual's social environment. This dissertation is the first study to develop more precise and nuanced measures for social integration including both personal and associational ties within ego networks concurrently.

The links between personal social networks and social integration are well-established, as are the links between voluntary association memberships and social integration (Babchuk and Edwards 1965; Berkman and Glass 2000; Campbell and Lee 1992; Falci and McNeely 2009; Hughes and Gove 1981; Seeman 1996). Relatively little is known, however, about how personal and associational ties reflect social integration when taken together. This is a notable limitation because an individual's social environment includes both personal and associational ties, but each type of tie may generate different consequences. For example, close personal ties to family and friends may provide support that differs from the support offered by church, sport, or literary groups. Additionally, personal and associational ties may differentially impact the structure of an individual's network (i.e., their level of social integration). Put differently, the loss of a close personal tie may have a stronger impact on an individual's social integration than the loss of an associational tie. Current research on social integration, however, cannot make such determinations.

In addition, our knowledge of who bridges social contexts, such as personal and associational networks, remains limited. Existing studies exploring the overlap in social contexts tend to be limited in three key ways: (1) studies do not directly measure the ties between personal and associational ties, beyond a binary indicator, (2) studies combine personal and associational measures into a single scale, omitting the nuanced patterns tying personal and associational spaces together, and (3) studies have identified who has shared contexts, but have not identified directly if named alters are also members of the same voluntary associations as an ego.

Therefore, this dissertation develops an innovative network structure—personal affiliation networks (PAN)—and a corresponding set of measures to more precisely social integration incorporating both personal and associational ties.

1.3 SUMMARY OF CHAPTER 2

To address the first two aims (Aim 1 and Aim 2), Chapter 2 develops a formal framework for measuring personal and associational ties simultaneously, building on the commonly used ego network data structure. Personal (ego) networks have been used theoretically and methodologically to capture the immediate social environment of individuals and to measure social integration. Ego networks tend to be limited to a single type of node (i.e., individuals), but researchers have identified many ways that social spaces overlap (e.g., crosscutting social circles, social foci, or the duality of persons and groups) (Breiger 1974; Feld 1981; Pescosolido and Rubin 2000; Schwartz 1997). Moreover, limiting ego networks to a single social context (i.e., personal ties) misses other important ties that make up an individual's immediate social environment.

Additionally, while actors (i.e., alters) in a personal network may hold multiple roles (e.g., friend and co-worker), typical studies do not directly measure if named alters are also tied to the voluntary associations in an ego's social environment. In many cases, this is due to insufficient data, as typical ego network studies fail to measure the social ties between actors and groups. Such studies often limit the immediate social environments of individuals to a single social context (i.e., personal ties), contrary to individuals' actual social environments, which encompass multiple social contexts at once. As a result, their measures of social integration may be imprecise. Although some methodological advances have been made that account for complex tie configurations, they cannot be applied to ego network data (Hollway et al. 2017; Zappa and Lomi 2015). To account for these methodological shortcomings, I develop a network structure that can be used to measure the shared personal and associational networks of individuals, which I define as personal affiliation networks (PAN).

Split into two main parts, Chapter 2 first identifies a PAN data structure and a series of measures to better capture social integration. After providing background information on social integration as currently measured by personal networks, voluntary associations, and the limited research exploring the two together, I introduce a PAN data structure. I then develop a series of measures, building from simple to more complex, to more precisely measure social integration, incorporating both personal and associational ties concurrently. A total of fifteen measures are developed, encompassed under four sets of measure types: (1) network degree, (2) network density, (3) co-membership specific, and (4) PAN cohesion. Overall, Chapter 2 provides an innovative methodological approach to traditional ego network research that I then use as a framework for the subsequent empirical chapters (Chapter 3 and Chapter 4).

1.4 SUMMARY OF CHAPTER 3

Chapter 3 relies on the 2006 National Voluntary Association Study (NVAS) as a case study for using the personal affiliation network (PAN) measures developed in Chapter 2 to explore individual social integration. The NVAS, a re-interviewed sample of the 2004 General Social Survey (GSS), was collected to better understand the role of voluntary associations in individual's lives and contains all features necessary to construct PANs: (1) the voluntary association memberships of respondents (egos), (2) their core personal networks, and (3) detailed information on how actors (alters) in their personal networks are tied to their voluntary associations. With data from the NVAS, Chapter 3 presents two main sets of analyses, aligning with Aim 3 and Aim 4.

The first set of analyses details the distribution of, and the relationship between, each PAN measure (Aim 3). After constructing the PANs of egos, I describe the distribution of each PAN measure across egos in the NVAS. Then, using bivariate statistics, I explore the relationship between simple measures of social integration (i.e., personal network degree, voluntary association degree, and personal network density) and the more detailed measures of social integration defined in Chapter 2.

In the first set of analyses, I identify four important findings about how PANs capture social integration and their relation to commonly used, simple measures of social integration. First, a high level of overlap exists between personal and associational contexts. This finding confirms that the common measures of social integration (e.g., network size and density) miss important aspects of the social world. Second, I find nuanced patterns in the structure and composition of PANs that are not uniform across each measure. Rather, measures that incorporate co-membership ties (i.e., alter-association ties) have unique features that highlight the integrating capacity of personal and associational ties, and the overlap between personal and associational social spaces.

The third main finding identifies the supplemental role that personal and associational ties play on social integration. Although personal networks and voluntary associations may integrate egos to different levels of society, their integrating capacities supplement each other: in some cases, associational ties may be able to substitute for personal ties, and vice versa. Finally, the fourth finding identifies structural differences in social integration between individuals with co-membership in their PANs and individuals without such co-membership. Egos with co-membership ties in their PANs differ on other networks measures, including simple network measures that only incorporate alters or alter-alter ties. For example, egos with co-membership ties in their wider PAN are associated with larger and denser personal networks, which indicates (1) the broader influence of social integration beyond personal ties and (2) the importance of including other social ties into social integration.

While the capacity of personal networks and voluntary associations to promote social integration have been highlighted in past research, it is still unknown precisely how social integration differs across demographic groups. Therefore, the second set of analyses draws on previous research to explore how a PAN approach could identify variations in social integration across demographic groups. First, I detail the NVAS sample, including information about the people and voluntary associations that compose PANs. Then, using bivariate and multivariate statistics, I explore the association between each PAN measure and ego demographic correlates (Aim 4).

When exploring demographic differences in social integration, two important considerations further emphasize the need to capture features of social life beyond personal ties. First, I find that, when using more precise measures, demographic variation in social integration does not fully align with previous findings. Rather, when incorporating personal and associational ties, differences across demographic groups are less stark than when using simpler measures of social integration: few differences exist when comparing sex, race, and education for PAN measures. This can be explained by personal and associational ties supplementing each other—by incorporating other types of ties, many group differences are washed out. Rather than using personal ties as the gold standard of social integration, other types of social connections (such as ties to associations) contribute to integration. This highlights the importance of expanding current measures of social integration to incorporate tie types other than personal ties. Without incorporating both personal and associational ties in measures of social integration, researchers may miss important nuances pertaining to the influence that social connections have on individuals and their health, well-being, and access to social support.

Finally, when looking at the social integration measures specific to co-membership ties (alter-association ties), I find few significant differences across demographic groups. Because group differences wash out with the inclusion of co-membership ties (alter-association ties), knowing the role of associational ties on social integration (particularly their bridging capacities) can inform research on social capital, social support, and other social integration correlates. Additionally, this finding highlights the role that alters have on our social environments more broadly—not only shaping how they are composed but also how they are structured. When considering the social properties of integration, this study postulates that ego demographics alone may not fully explain what binds personal and associational contexts. Rather, research needs to focus on other compositional characteristics—namely, how alters influence social integration.

1.5 SUMMARY OF CHAPTER 4

Taking up the questions left at the end of Chapter 3, Chapter 4 extends beyond the ego-level to the alter-level, exploring the influence that alters have on integrating an ego's personal affiliation network (PAN). Focusing on Aims 5 and 6, this study described in this chapter identifies alter tie characteristics that predict the influence an alter has on an ego's PAN structure, where influence is measured as a percentage change in the PAN measure when ties from a given alter are removed. This dyadic analysis informs research on social integration by identifying (1) key alters who have the most influence on integrating PANs and (2) how an alter may influence an ego's network structure.

This study also uses the 2006 NVAS data, the same dataset used in the previous study (Chapter 3). For these analyses, however, I use only a subset of egos: those that have co-membership ties within their PANs (n = 393). Because the main goal of this study is to identify the influence alters have on social integration, particularly when using better measures of social integration, I focus only on PANs where alters have an influence on the connections between personal and associational ties.[1] Using univariate, bivariate, and multivariate statistics, I present a dyadic analysis (alters nested within egos) to explore how the tie characteristics (homophily, tie type, tie strength, and co-membership) of 1,478 alters influence PAN structures.

[1] While alters of egos with no co-membership ties can differentially influence an ego's integration on measures specific to personal ties (alter-alter ties), alters would not differentially influence the co-membership-specific measures containing alter-association ties, as no alters shared memberships to any of the ego's voluntary associations.

Four major findings from this study highlight the important role that alters have in integrating PANs. First, I find that overlap in personal and associational contexts is more highly influenced by similarly aged alters. Alters whose age is are more similar to that of an ego have higher expected influence on PAN structure, specifically for co-membership measures. This suggests that associations where egos share more co-membership (alter-association) ties are age homophilous. This finding further emphasizes that complexity of social bonds, where ties to associations are likely with similarly aged people.

Second, I find that spouses are more influential in structuring PANs compared to other kin and non-kin alters. This finding holds across all PAN measures. Although previous research has established the role of spouses in shaping personal networks and their consequences for individuals (Cornwell 2012; Uchino et al. 2013), these explorations have not extended beyond personal ties. While my research confirms that spouses do highly influence the integration of personal networks, this study also highlights their importance for integrating other social spaces. The influence of spouses in the personal and associational aspects of an individual's network can, on the one hand, provide important social support, as a spouse more clearly understands and knows their partner's support needs. But, on the other hand, the loss of spousal ties may result in significant fragmentation of personal and associational ties, as spouses integrate not only personal networks but broader PANs as well.

The third finding also highlights how social integration is influenced not only by the number of social ties but also by the quality of ties. Focusing on the strength of ties, I find that strong ties are more influential, although the extent of the influence depends on the PAN measure (focusing either on personal ties, co-membership ties, or the combination of both). Specifically, for PAN measures containing either personal ties or the combination of personal and associational ties, longer established ties and more frequent interactions with alters have a high influence. For the co-membership-specific measures (isolated to alter-association ties), however, the length of the relationship with an alter is not a significant predictor of an alter's influence. These nuances provide important insights into social integration within a PAN context: although associational ties can substitute for personal ties, the integrating mechanisms of ties operate differently for the two types.

Fourth and finally, I identify that the context in which ties form shapes integration in complex ways. For the co-membership-specific measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members), having met an alter in an association is associated with lower overall influence of that alter. This finding highlights the differential roles that alters and associations play in integration: associational ties are weak ties, whereas personal ties are stronger. Put differently, meeting an alter in an association, while potentially strengthening the tie to that specific association, influences neither personal integration nor other alter-associational ties. Meeting an alter in an association creates a siloed integrated space that does not bleed into other social spaces in an individual's social environment.

Overall, this chapter extends beyond individual attributes influencing social integration to the ties that bind an individual's social world. Recognizing which features of social ties influence PAN structure has larger implications for research focusing on social integration. Knowing that spouses and frequently activated ties, for example, are influential in integrating PANs can be useful to researchers exploring social support, as it may help them understand the salient roles and processes consequential for social integration. Additionally, practitioners and communities can use these findings to shape interventions aimed at providing support and increasing the social integration of individuals.

1.6 SUMMARY OF CHAPTER 5

The final chapter of this dissertation integrates all three studies, discusses the general implications of these findings, and pinpoints future avenues for research on social integration. Core features connecting all three studies are (1) personal affiliation networks (PANs), the innovative data structure developed in the first study to incorporate both personal and associational ties with ego networks, (2) a series of more detailed measures of social integration that build on already established, simpler measures, and (3) a theoretical framework linking personal networks, voluntary associations, and the combination of the two to social integration. Taking all three core features together, this dissertation provides a framework for measuring social integration in a more detailed and nuanced way that better captures the complexities of social life.

More generally, the framework developed in this dissertation can be used to answer questions central to sociology, including which social connections foster social integration and how social ties are consequential for individuals. Overall, I suggest that social integration can be better understood when incorporating more detailed information about the social ties that structure social life—namely, the social ties that individuals have beyond personal ties and the overlap between different types of ties. I end by discussing extensions of this framework and its general importance.

CHAPTER 2 MEASURING SOCIAL INTEGRATION

2.1 INTRODUCTION

Social integration is achieved through relationships that connect individuals to each other and to collective groups, and it influences individual outcomes from health and psychological well-being to economic opportunity and political engagement (Berkman and Glass 2000; Blau 1960; Friedkin 2004; Marsden and Friedkin 1993; McCarty 2002; Perry and Pescosolido 2010; Simmel 1955; Smith and Christakis 2008). Past work, for example, has found that those who are less integrated (i.e., lacking social connections) are at higher risk for depression, suicidal ideation, and other poor mental health outcomes (Cacioppo and Hawkley 2003; Cornwell and Waite 2009). Individuals are integrated into society at different levels: At the micro-level, individuals are connected to each other, for example, as friends, family members, and confidants. At the meso-level, individuals are connected to institutions through their active participation (Bearman 1991; Breiger 1974; Pescosolido and Rubin 2000; Simmel 1955). Methodological developments in measuring social integration have proceeded along two largely distinct lines: (1) research on personal (ego) networks that focuses on measuring the relationships between individuals and (2) research on voluntary associations that focuses on the connections between individuals and collectivities. However, measures that integrate both are currently lacking.

Personal (ego) networks operate as a window into the interpersonal social environment of individuals and are used to measure how integrated individuals are (Berkman et al. 2000; Seeman 1996). They consist of an ego (i.e., an individual) and their nominated alters (e.g., close friends, discussion partners, or confidants) (Perry et al. 2018; Smith 2019). Research using ego networks has emphasized *composition* (who our alters are) and *structure* (how alters are connected) as two components necessary to understand individual and social outcomes (Mollenhorst, Völker, and Flap 2012; Perry et al. 2018; Vacca 2019). Structural properties of ego networks have been used to predict many outcomes, such as physical and mental health, life satisfaction, and economic opportunity (Cornwell 2009; Cornwell and Waite 2009; Perry and Pescosolido 2010; Perry et al. 2018; Smith, McPherson, and Smith-Lovin 2014). Studies have found that one's social ties and the larger features of one's personal social network influence both the effectiveness and the utility of the social support one receives (Agneessens, Waege, and Lievens 2006; Ashida and Heaney 2008; Berkman and Glass 2000; Wellman and Wortley 1990).

Similarly, voluntary associations, typically defined as formally organized groups to which members are not fiscally bound (e.g., book clubs, sport clubs, church groups) (Bonikowski and McPherson 2007; Knoke 1986; Knoke and Thomson 1977) play an important role in shaping individual behavior (Paxton and Rap 2016)and have been called the building blocks of society (Tocqueville 2003). Voluntary associations link individuals to collective events (Wellman and Wortley 1990), thus shifting the focus of social ties from the personal to a broader associational level. They create, maintain, and reinforce values, institutions, and practices (Wellman and Wortley 1990). From a Durkheimian perspective, voluntary associations operate as both integrative and regulatory spaces (Berkman et al. 2000). Voluntary associations can create social cohesion within communities, mobilize resources, and regulate norms and practices (Benton 2016; Bonikowski and McPherson 2007; Booth and

Babchuk 1969). At the individual level, membership in an association provides key benefits such as access to broader support (i.e., economic, emotional, and mental well-being), but associations can simultaneously operate as exclusionary, primarily homogenous, spaces (Davis, Renzulli, and Aldrich 2006; McPherson 1983; Popielarz and McPherson 1995).

Although personal networks and voluntary associations have been used to measure social integration, little research has brought the two together, and the few studies that have combined personal and associational ties have done so in a limited way. For instance, personal and associational ties have been explored together using full (sociocentric) network data (Lomi, Robins, and Tranmer 2016; Zappa and Lomi 2015). While such approaches have the data structure and established methodological techniques needed to measure personal and associational ties simultaneously, the data tend to be limited to a single case and are not widely available. More commonly, researchers rely on sampled ego network data (Perry et al. 2018; Smith 2019), but the methodological techniques used to combine personal and associational ties for full network data cannot be applied to ego network data.

A limited amount of research using sampled data has explored both personal and associational ties (Cornwell and Waite 2009; McPherson, Smith-Lovin, and Brashears 2006; Musick and Wilson 2003; Ziersch and Baum 2004; Zunzunegui et al. 2003). One main limitation of these studies is their inability to measure the dependence between personal and associational ties. While people with close personal relationships may also be co-members of the same voluntary associations, sampled ego network surveys do not typically measure such ties—that is, they do not indicate whether the nominated alters are members of the same voluntary associations as the ego. Constrained by how the data are structured, studies using sampled data take one of three approaches: (1) combining personal and associational ties into a single scale (Cornwell and Waite 2009), (2) using one type of tie as a control variable when predicting the other (Musick and Wilson 2003; Ziersch and Baum 2004; Zunzunegui et al. 2003), or (3) treating co-membership as a single type of role relation (akin to spouse, friend, or neighbor) (McPherson et al. 2006).

These existing studies fail to capture the overlapping structure of personal and associational ties. Because of methodological limitations caused by the use of sampled ego network data and the inability to adequately account for dependencies between personal and associational ties, current studies miss crucial aspects of social integration. For example, research to date cannot identify whether an individual with few nominated alters is socially integrated in other ways, such as by having a tightly knit group of alters who are co-members in the same voluntary associations. Put differently, the extent to which overlapping personal and associational ties contribute to social integration remains unknown and unexplored.

The primary aim of this chapter, therefore, is to propose a conceptual framework and corresponding measures linking personal and associational ties using sampled ego network data. I ask two main research questions: (1) How can personal and associational ties be linked using sampled ego network data? (2) What are possible ways to measure social integration by linking personal and associational ties? I begin with a short background on personal networks, voluntary associations, and the importance of examining the two together. I then conceptualize the data structure needed to pair personal and associational ties in the context of ego networks. Finally, I introduce a set of measures that retain information about both the personal and associational ties of individuals.

2.2 BACKGROUND

2.2.1 Personal Networks and Social Integration

Ego network data have been used to incorporate relational dynamics within traditional survey data (Perry et al. 2018; Smith 2019). While typical survey data measure the attributes of each respondent, social network data measure how individuals are connected to one another. More specifically, ego network data focus on a sample of individuals and the close interpersonal relationships that constitute their immediate social world. These data allow us to measure relationships between an ego (or individual) and alters (those close to the ego), such as close friends, discussion partners, or confidants (Campbell and Lee 1991; Marsden 2003; Perry et al. 2018; Smith 2019; Straits 2000).

The people on whom we rely to provide instrumental and emotional support are those with whom we discuss important matters (Verdery and Campbell 2019; Wellman et al. 1991). These people, with whom we have the strongest and closest ties (Marsden 1987; McPherson et al. 2006), are the core members of our personal networks; they constitute our social environment and are used to measure individual social integration. Our core discussion partners offer access (or potential access) to a broader range of support (Wellman and Wortley 1990) and have influence—both directly (through interactions) and indirectly (through norms and social influence)—on the types of people that we become (Marsden and Friedkin 1993; Smith-Lovin and McPherson 1993).

For decades, sociologists have been investigating the structure and composition of discussion networks (Marsden 1987; McCarty 2002; McPherson et al. 2006; Smith et al. 2014). Both our alters (i.e., composition) and the connections between our alters (i.e., structure) have implications for individual and social outcomes (Mollenhorst et al. 2012; Perry et al. 2018; Vacca 2019). Previous studies have aimed to create a typology describing the structural configuration of personal networks across a sample (Bidart, Degenne, and Grossetti 2018; Giannella and Fischer 2016; McCarty 2002; Vacca 2019). Larger networks, for example, have been found to have positive effects on a variety of outcomes such as mental health and well-being (Haines and Hurlbert 1992; Smith and Christakis 2008). More network ties, however, are not always better. Many negative ties, for example, can have a negative impact on outcomes. Additionally, even in networks with generally positive ties, maintaining a large number of connections can, in itself, be a burden to an ego. In the ego network context, the size of one's network is commonly used as a measure of social support (Umberson and Karas Montez 2010; Verdery and Campbell 2019). It can be used within the context of a single ego or aggregated to describe the degree distribution across a sample of egos (Smith 2019). Additionally, network size is the foundation for many more complex measures used to understand group cohesion and the structural characteristics of a network, including the patterning, strength, and density of interpersonal ties (Friedkin 2004).

Additionally, variability in the structure and composition of personal networks has been explored across egos, where gender, race, age, and other sociodemographic characteristics are indicative of different network characteristics. For example, men are more likely to be socially isolated than women (McPherson et al. 2006); women tend to be closer emotionally to the people in their families—receiving more social support from their family relationships than men do (Verdery and Campbell 2019). The close networks of older adults rise until middle age, after which they begin to decline (Smith et al. 2015). More highly educated egos tend to have larger, more diverse networks containing a lower proportion of alters who are kin (McPherson et al. 2006). Education and income also influence access to relational resources (Verdery and Campbell 2019).

While the structure and composition of personal networks have been used as a primary context for understanding social integration, these data rarely extend beyond the level of the individual. We know, however, that social interactions occur in many different contexts and may include people who are core to our personal networks. For example, an alter may also be a co-worker, spouse, or co-member of an organization. Understanding how our personal networks overlap with other spaces in our social environment is essential to understanding social integration more fully.

2.2.2 Voluntary Associations and Social Integration

Voluntary associations are formally organized groups that create, maintain, and reinforce values, institutions, and practices (Bonikowski and McPherson 2007; Knoke 1986; Knoke and Thomson 1977; McPherson 1983; Wellman and Wortley 1990). Such associations include political groups, sports clubs, and religious communities. Voluntary organizations serve a variety of expressive and instrumental purposes (Bonikowski and McPherson 2007; Booth and Babchuk 1969; Rotolo 2000).

Voluntary associations have individual and societal benefits (McPherson 1983; Rotolo 1999). Previous research has examined the correlates and consequences of voluntary association membership from individual and organizational levels. Social participation—whether participating in a voluntary association such as a book club or volunteering at a local nonprofit—is associated with better subjective well-being (Thoits 2012), decreased loneliness (Niedzwiedz et al. 2016), and delayed cognitive decline in older adults (Glass et al. 2006). Groups impose normative or moral demands on their members that can shape individuals' identities, create a sense of belonging, and even regulate behaviors (Bearman 1991; Booth and Babchuk 1969).

Aggregate trends suggest that voluntary association membership has declined over time (Knoke and Thomson 1977; Putnam 2000b). For instance, participation in church-related groups, while high (Cutler and Hendricks 2000; Wellman and Wortley 1990), has decreased over time (Rotolo 2000). Other studies have found an increase in specific types of participation (Painter and Paxton 2014), such as professional, service, and hobby groups (Rotolo 1999, 2000).

Additionally, the associative habits of individuals tend to vary demographically. Individuals who are church-affiliated, for example, tend to participate in other voluntary associations at higher rates than those who are not part of religious communities (Cnaan, Boddie, and Yancey 2003; Taylor and Chatters 1988). Individual networks are likely to be more diverse as the number of voluntary associations within the network increases (Davis et al. 2006; McPherson, Popielarz, and Drobnic 1992; Musick and Wilson 2003; Popielarz and McPherson 1995; Rotolo 2000). This is because memberships increase access to social network ties (or at least potential ties). Those with more education and higher incomes are likely to be involved in a broader set of associations (Sandstrom and Alper 2019), just as they are likely to have larger personal networks.

2.2.3 Why Combine the Personal and the Associational?

Although research has established the integrating and regulating roles of personal networks and voluntary associations, this work has rarely analyzed both together. Personal networks and voluntary associations may share common ties—those with whom we are close interpersonally may also be members of the same voluntary associations as we are. In fact, this dual relationship between individuals and groups has been a hallmark of sociology (Breiger 1974; Durkheim 1951; Feld 1981; Friedkin 2004; Marsden and Friedkin 1993; Simmel 1955). While different networks serve different purposes (Bidart and Degenne 2005; Perry et al. 2018), our social interactions crosscut social circles (Schwartz 1997; Simmel 1955), construct foci based on shared activities (Feld 1981), and more generally constitute our social environment (McFarland et al. 2014).

While our social environment consists of both interpersonal and organizational connections, typical network studies, especially those focused on personal network research, do not take up both (Mollenhorst et al. 2012). The recent research that does analyze both individual and organizational ties—two-mode (bipartite) networks and multilevel network analysis (MNA)—typically relies on full network data and methodological techniques that cannot be translated to sampled ego network data (Field et al. 2006; Lomi et al. 2016; McPherson 1982; Wasserman and Faust 1994; Zappa and Lomi 2015).

The studies that use sampled data to incorporate personal and association ties do not measure their dependencies directly and have other shortcomings: (1) individual and organization ties are often reduced to a single scale (combining both the personal and associational) (Cornwell 2012; Cornwell and Waite 2009), (2) information about each tie type is included only as a covariate (i.e., the ties are assumed to be independent of each other) (Musick and Wilson 2003; Ziersch and Baum 2004; Zunzunegui et al. 2003), or (3) a shared context is treated as a dichotomous relational tie type (i.e., "co-member") (McPherson et al. 2006; Wellman and Frank 2017).

First, reducing personal and associational ties to a scale may fail to adequately describe how core membership partners are involved in other areas of an individual's social environment. Cornwell and Waite (2009), for example, combine personal and associational measures into a scale in order to capture the social disconnectedness of individuals, the inverse of social integration. Their scale combines social network characteristics, a general measure of friendship size (how many friends do you have?), and social participation. The social network characteristic in the scale includes network size, network range (the number of different relationship types), rate of interaction, and proportion of network members living with an ego. Social participation included three frequency measures of participation, including the frequency of attending meetings, socializing with friends and relatives, and volunteering. While their scale can better assess the overall connectedness of individuals, it misses key granularities about where connections occur and the ways in which social networks and social participation may overlap.

Similarly, while other research incorporating personal and associational contexts together emphasizes the importance of overlapping, shared contexts, it misses more detailed patterns of how individuals and associations are tied together (Davis et al. 2006; McCarty 2002; Mollenhorst, Völker, and Flap 2011; Mollenhorst et al. 2012). For example, Mollenhorst et al. (2011a) find that, on average, people share two contexts with their network members. Additionally, in another study, they find that context overlap influences triadic closure in discussion networks (Mollenhorst et al. 2011). Triadic closure often provides denser, more tightly coupled relationships that strengthen the integration of individuals into a larger environment, reducing possible network fragmentation. Neither of these studies, however, measures the extent of overlap within personal networks. Rather, context sharing is reduced to a binary indicator (i.e., shared versus not shared), which misses key information about the extent of overlap that exists within an individual's larger network.

Finally, research that has incorporated how multiple contexts are shared—where an alter is also a member of an ego's voluntary association(s)—has been limited to a single role relation (e.g., "co-member"), which ultimately misses the heterogeneous and multiplex nature of co-membership ties. Reducing a relational type to a binary indicator may miss important granularities about specific types of ties, some of which have multiple, potentially heterogeneous roles. Although a single role relation is useful in identifying a type of relation like "spouse" or "co-worker," for example, its utility is lost when the role relation being measured is not a binary category. While multiplex ties have accounted for the multiple roles that a person can have (e.g., your spouse is also one of your co-workers), these ties tend to be *between* different types of relations (e.g., friend and co-worker).

Less work has explored the multiplexity within a single role relation. This is important, particularly for roles that may have many, possibly heterogenous, positions. For example, a person can be a member of many different types of associations, and that person's alters may be members of none, some, or all of them. Only accounting for a dichotomous "co-member" tie, defined as a single type of relation (see McPherson et al. 2006 for an example), does not account for the possible heterogeneity and multiplexity comprising a "co-member."

Even though other role relations could feasibly have multiple types of the same tie, their purpose tends to be more homogeneous. For instance, in the case of a person with multiple jobs, the single relation of "co-worker" may not identify the multiple roles but still captures the same relational elements. If we assume that co-worker roles operate similarly across multiple work contexts, then a single "co-worker" relation will suffice. This assumption, however, may not hold if the contexts under consideration are highly heterogeneous. Say, for instance, that an alter is a co-member in three associations—a church group, a book club, and a political group. Each of these associations may have a different ideology, a different level of influence, and different access to resources that a single "co-member" relational tie cannot fully capture.

Overall, these studies highlight the need to directly measure the connections between personal and associational contexts as well as to develop methods that can be applied to sampled ego network data. Failing to measure the connections between the people with whom we are close and our voluntary association memberships may lead us to miss important mechanisms influencing social integration and individual outcomes. For example, if those that with whom we are most close are also members of our voluntary associations, this added layer of embeddedness may uniquely contribute to broader social integration. Additionally, social isolation (i.e., lack of interpersonal ties) may not be detrimental if, for example, an ego is highly involved in voluntary associations. To better measure the structure and composition of social environments, advances need to be made in data collection and measurement construction to bridge the personal and the associational.

To that end, this chapter identifies a possible data structure that captures connections between individual and organizational ties using sampled ego network data. Additionally, drawing on traditional network measures, I introduce measures to more precisely capture the overlap between the personal and associational. In the following two sections, I detail the methodological considerations needed for measuring personal and affiliation ties together by (1) identifying the necessary data structure needed to connect alters and voluntary associations and (2) deriving key measures—building from simple to complex—to capture these connections.

2.3 METHODS

2.3.1 Typical Ego Network Data

Ego network data typically contain four main pieces of information: (1) the attributes of the ego (i.e., the respondent), (2) alters (the people that ego is connected to), (3) alter-specific information (demographic attributes and attributes of the ego-alter relationship), and (4) alter-alter information (information about the relationships between alters) (Campbell and Lee 1991; Marsden 1990; McCarty 2002; Perry et al. 2018; Smith 2019; Vacca 2018).

Most closely related to typical survey data, ego characteristics can be used to compare differences across egos as well as to inform how different attributes of the ego are associated with the composition and structure of the network. Attributes specific to the ego include demographic characteristics (e.g., sex, race, age), attitudes, ego-specific outcomes (e.g., social support, health, well-being), and other explanatory variables (Marsden 1990; McCarty et al. 1997; McPherson et al. 2006).

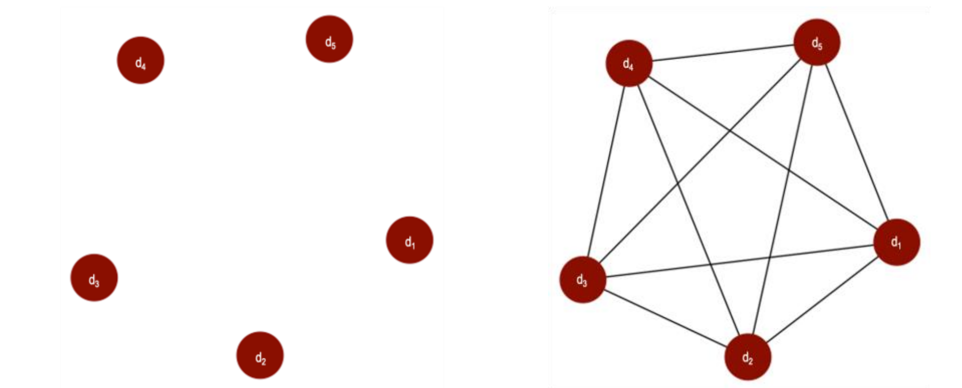
Additionally, ego network data contain relational characteristics about individuals who are part of the ego network. Name generators, such as close confidants or those with whom you discuss important matters, are used to enumerate alters that constitute a person's immediate social environment (Campbell and Lee 1991; Marsden 1990; McCarty et al. 1997). Name interpreters, in contrast, provide information about alters, including demographic attributes (e.g., role relation, gender, race) and tie characteristics (e.g., frequency of contact, social support) (Eagle and Proeschold-Bell 2015; Perry et al. 2018).

Ego network surveys may also contain information about the ties between alters (Smith and Gauthier 2020). While typical ego network data measure persons close to the respondent, surveys are increasingly measuring the interpersonal ties between respondents' alters. Known as alter-alter ties, these connections provide added information beyond dyadic connections between egos and their close neighbors. Ties between alters inform the structure and patterning of the personal relationships in which an ego is embedded (Marsden 1993).

A sampled ego network dataset may include hundreds or more egocentric networks and can be visualized as seen in Figure 2.1. Here, the nodes (red circles) represent an ego's nominated alters, and the edges depict the alter-alter ties. The ego (i.e., the individual respondent) is not included in the graph because, definitionally, the ego is tied to every nominated alter.

Figure 2.1 Example Ego Networks

A. Ego Network without Alter-Alter Ties **B.** Ego Network with Alter-Alter Ties



= Alter
= Alter-Alter Ties

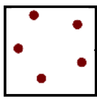
While the visualization of ego networks is useful to picture how they are structured, the calculation of network measures relies on the underlying adjacency matrix (**X**) from which each projection is made. Table 2.1 presents two adjacency matrices corresponding to each ego in Figure 2.1. Because ego network data tend to be undirected, **X** is a symmetric g-by-g matrix where each alter has a corresponding row and column, the diagonals are undefined, and each alter *I* and *j* pair capture the ties between alters (Wasserman and Faust 1994).[2] A "1" defines a tie between the

[2] The ties between the ego and alters are not represented because it is assumed that there is a tie between the ego and every nominated alter (McCarty 2002; Perry, Pescosolido, and Borgatti 2018).

two alters, whereas a “0” indicates the absence of a tie. The adjacency matrix **X**a contains all zeros, given that no alter-alter ties are measured. The second matrix (**X**b) is just the inverse, where all ties are present between alters.

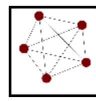
Table 2.1 Personal Network Adjacency Matrices

A. Ego Network without Alter-Alter Ties



$$\mathbf{X}_a = \begin{array}{c} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{array} \begin{array}{ccccc} d_1 & d_2 & d_3 & d_4 & d_5 \end{array} \begin{bmatrix} - & 0 & 0 & 0 & 0 \\ 0 & - & 0 & 0 & 0 \\ 0 & 0 & - & 0 & 0 \\ 0 & 0 & 0 & - & 0 \\ 0 & 0 & 0 & 0 & - \end{bmatrix}$$

B. Ego Network with Alter-Alter Ties



$$\mathbf{X}_b = \begin{array}{c} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{array} \begin{array}{ccccc} d_1 & d_2 & d_3 & d_4 & d_5 \end{array} \begin{bmatrix} - & 1 & 1 & 1 & 1 \\ 1 & - & 1 & 1 & 1 \\ 1 & 1 & - & 1 & 1 \\ 1 & 1 & 1 & - & 1 \\ 1 & 1 & 1 & 1 & - \end{bmatrix}$$

Ego network data provide detailed information about the social and structural context in which individuals are embedded, inform extant research on interpersonal social interactions and integration, and are easily collected using standard, general population surveys (Giannella and Fischer 2016; Marsden 1987; Perry et al. 2018; Smith 2019). However, such data rarely extend beyond a single node type.

The main limitation of sampled ego network data is its omission of ties between other node types. Because ego network data typically focus on social ties between individuals, they cannot be used to measure how interpersonal relationships operate beyond one’s core network. Individuals, however, may be connected with their core network members in other ways beyond the personal. This is especially evident when you consider voluntary associations. Incorporating additional tie relations, both personal and associational, between egos and their alters provides important precision to the measurement of social integration. In the next section, I introduce a multi-node network structure in an ego network context.

This unique ego network data structure, which utilizes typical ego network survey design, can capture the dependencies between personal networks and voluntary associations that extend beyond a single relational type (i.e., co-member).

2.3.2 Personal Affiliation Networks (PAN)

Because I am interested in measuring the overlap between the personal and the associational, my goal is to retain as much information about the structure and composition of an individual's social environment as possible. If we assume that personal networks and voluntary associations can be linked, we can derive a data structure that captures the possible ties both *within* and *between* both node types. That is, we can capture alter-alter ties within a single node type and alter-association ties across node types. Building on a typical ego network data structure containing information on alter-alter ties, I propose adding voluntary associations as a second node type. The addition of this second node type introduces two additional pieces of data: (1) voluntary association memberships and (2) ties between alters and associations (i.e., co-membership).

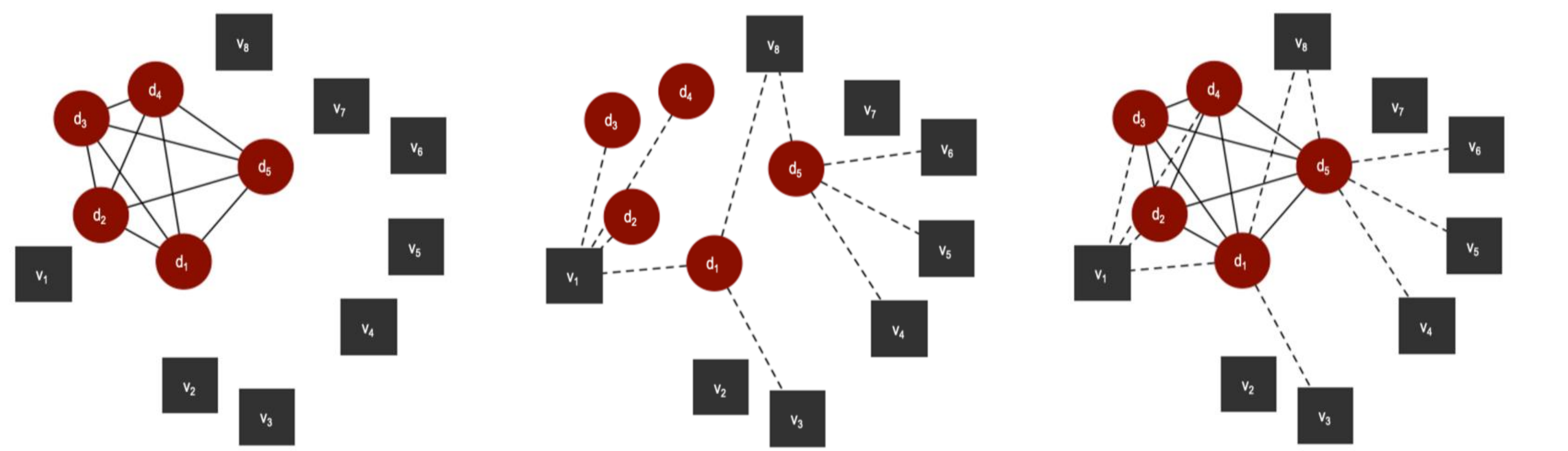
Many studies, such as the General Social Survey (GSS), already measure the associative habits of individuals as an ego-level characteristic. The voluntary association memberships elicited by such studies have been used to explore trends in the types of organizations in which people participate and the magnitude of their participation (Bonikowski and McPherson 2007; Rap and Paxton 2018; Rotolo 1999). Within the context of a personal network, voluntary association memberships can be treated as another degree measure, capturing the size of an ego's voluntary association network. In the simplest case, voluntary association size can be used as a second type of node within a person's immediate social network. Here, however, unlike in most ego networks, the node represents a group and not an individual. This case is depicted in the first pane of Figure 2.2 (network A), where all ego network information is retained (including alter-alter ties) but voluntary associations are included as additional nodes within the network (denoted by gray squares).

Once we incorporate voluntary associations as a node type, we can also derive the ties between alters and associations, defined as co-membership ties. Alter-to-alter ties, in the traditional ego network case, measure the social relationships between the alters. Co-membership ties (i.e., ties between alters and voluntary associations) measure whether alter *I* is a member of organization *j* to which the ego is also a member—integrating the personal and associational. There may be many important conceptual benefits to measuring co-membership ties. These ties, for example, can be used to inform how the personal and associational overlap, identify whether particular associations have higher concentrations of overlap, and differentiate different levels of individual integration. The middle pane of Figure 2.2 (network B) illustrates a co-membership network where alter-alter ties are not included and the focus is limited to the ties between alters and associations (represented by a dashed line).

The patterning of co-membership ties can identify how much overlap exists between the personal and associational environments of an individual. For example, in network B (Figure 2.2), we can see that one organization has many co-members and that two alters have a high overlap in associational memberships with ego. Knowing the extent of overlap and what types of associations have a higher concentration of overlap, for example, can improve our understanding of social integration and social support.

Figure 2.2 Example Personal Affiliation Network Varying by Tie Type Inclusion

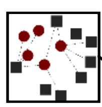
A. Personal Network | B. Co-Membership Network | C. Personal Affiliation Network



● = Discussion Partner
■ = Voluntary Association
— = Alter-Alter Tie
- - = Co-membership Tie (alter–association tie)

Measuring co-membership in standard sampled ego network surveys can be easily achieved using similar techniques for gathering information about the ties between alters. As a first step, a voluntary association membership could be added as an additional element beyond the elicitation of alters. Second, for each alter, we could ask about co-membership (as a standard role relation) and follow up with the specific alter-associational ties limited to the set of voluntary association memberships previously identified by the respondent. For surveys that already elicit the associative habits of individuals, the only added step would be the addition of alter-association tie elicitation, as co-membership is often already captured as a role relation type (see the GSS, for example).

Table 2.2 Co-Membership Network Affiliation Adjacency Matrix



$$\mathbf{A} = \begin{array}{c} \\ d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{array} \begin{array}{c} \begin{array}{cccccccc} v_1 & v_2 & v_3 & v_4 & v_5 & v_6 & v_7 & v_8 \end{array} \\ \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \end{bmatrix} \end{array}$$

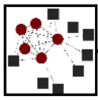
The data structure of a co-membership network (network B; Figure 2.2) can be captured in an affiliation adjacency matrix (**A**) (see Table 2.2). The affiliation adjacency matrix (**A**) is a d-by-v matrix, where rows are nominated discussion partners (d) and columns are voluntary association memberships (v). Though the affiliation adjacency matrix (**A**) retains information about how personal ties are connected to associations, the personal network characteristics—specifically, alter-

alter ties—are lost. This is important if we suspect that the structure and composition of a person's personal network may influence their associative habits, for example.

Typically used in bipartite (or two-mode) networks, an affiliation adjacency matrix denotes the ties between actors and events (Wasserman and Faust 1994). The main assumption about two-mode networks is that actors are not directly connected to each other. Rather, actors are only connected through shared affiliations (or the second mode). Actors are not represented as interacting with each other, but rather are linked through shared participation. Similarly, for affiliations, the group is defined only through characteristics of the set individuals (or members) involved. One of the clear benefits of bipartite networks, therefore, is their ability to represent the duality of individuals and groups (Breiger 1974). While a bipartite approach more fully captures the overlap between individuals and groups, where individuals constitute the groups of which they are members, it is typically applied to full, sociocentric data where ties between individuals are not known. Given that ego networks have both ego-alter and alter-alter ties, limiting the co-membership network to co-membership ties alone does not retain information about the personal network of the ego.

Pairing typical ego network data with voluntary association membership and co-membership ties in a unique, multi-node, multi-tie data structure, which I define as a personal affiliation network (PAN), retains as much information as possible about an individual's social environment. The third network in Figure 2.2 (network C) depicts such a data structure, which connects the personal and the associational. A full PAN data structure retains information about the respondent (ego), their alters, their associative habits, the connections *within* alters, and the connections *between* alters and associations.

Table 2.3 Personal Affiliation Network (PAN) Adjacency Matrix



$$\mathbf{P} = \begin{array}{c} \\ d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \\ v_8 \end{array} \begin{array}{c} \begin{array}{ccccccccccccc} d_1 & d_2 & d_3 & d_4 & d_5 & v_1 & v_2 & v_3 & v_4 & v_5 & v_6 & v_7 & v_8 \end{array} \\ \begin{bmatrix} - & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & - & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & - & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & - & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & - & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & - & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & - & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & - & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & - & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & - & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & - & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & - & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & - \end{bmatrix} \end{array}$$

Likewise, a PAN data structure can be highlighted in an adjacency matrix (**P**) retaining all known/available information about the personal and associational ties of a given ego. A PAN adjacency matrix (**P**), in essence, combines the personal ($\mathbf{X}_b$) and the co-membership (**A**) adjacency matrices. Table 2.3 displays the PAN adjacency matrix (**P**), a square dv-by-dv matrix where each discussion partner and voluntary association have a corresponding row and column. As in the case of the typical ego network, the diagonal is undefined, and a tie between any node combination (alter or association) is represented by a “1” and the lack of a tie by a “0.” This data structure, therefore, has information about alters, associations, alter-alter ties, and co-membership ties (alter-associations). In Table 2.3, for example, **P** contains both d_n and v_m rows and columns corresponding to the total number of discussion partners and voluntary associations nominated by ego. We can see, as in the corresponding network visualization (panel 3 of Figure 2.2), that the ego's first discussion partner (d_1; row 1) is tied to all four alters (d_2-d_5; columns 2-5) and is a co-member in three of the ego's eight voluntary associations.

In an ideal case, we would also be able to gather information about the ties between voluntary associations. However, because of the nature of sampled ego network data, that is not possible. If we had information about the ties both between and within each node type, more sophisticated techniques could be implemented, such as multilevel network analysis (see Zappa and Lomi 2015, for example). With sampled ego network data, we are limited to indirect connections between voluntary associations when there are shared members. Therefore, given the square nature of the PAN adjacency matrix (**P**), association-association ties are always assumed null. This distinction is highlighted by a red box in Table 2.3, focusing on the association-association ties. In the ego network context, association-association connections may not be an important tie type. Because personal networks capture a social environment from an individual's perspective, how associations are organizationally linked may not matter that much. For individuals, the more important distinction may be how core network members connect voluntary associations. These connections are retained through co-membership ties, which is an additional benefit of a PAN data structure.

One main challenge of using a multi-node data structure, especially using sampled ego network data, is the lack of empirical tools to incorporate both modes together in a single measure (Wasserman and Faust 1994). Even with recent methodological advances, few studies extend the dual nature two-mode data to sampled ego network data (Doreian, Lloyd, and Mrvar 2013; Field et al. 2006). In the section that follows, I introduce traditional and new network measures designed explicitly using a PAN data structure. As depicted in the far column of Figure 2.2 (network C), a PAN data structure constructs a more fleshed-out picture of an immediate social environment that can be fully captured neither by looking solely at personal networks nor by using only co-membership ties. In an attempt to establish better measures to capture personal and associational dimensions together, I detail measures that deviate from traditional ones (e.g., degree and density) and identify others to explicitly capture patterns of co-membership.

2.4 MEASURES

Various summary measures have been used to capture the structure and composition of personal networks (Bernard et al. 1990; Marsden 1993; Perry et al. 2018). Here, I modify traditional measures to account for the multi-node and multi-tie structure of personal affiliation networks (PAN). By incorporating both ties between alters and ties between alters and voluntary associations (i.e., co-membership), key information about the dependencies between interpersonal and organizational social environments is retained. In order to account for this additional information, I derive structural measures (i.e., size, density, and cohesion) and compositional measures (i.e., rates and concentration of co-membership) designed for the PAN data structure.

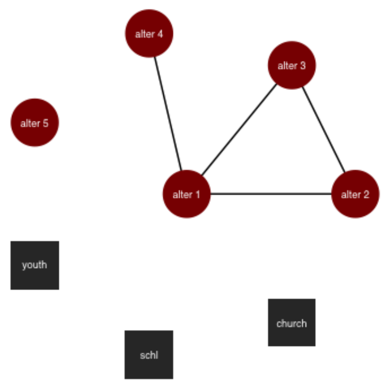
For each network measure detailed below, I use a toy network to demonstrate how it is constructed. Table 2.4 presents the network projection and corresponding adjacency matrix for a toy network displayed in three ways. Each network projection is based on the same ego, who has five alters (noted by red circles) and three voluntary association memberships (noted by gray squares). Each network varies by the inclusion of different tie types retained in a PAN data structure. The first block of Table 2.4 is the personal ego network, containing only ties between alters. The second block projects the co-membership network of the ego, containing only alter-organizational ties. Finally, the third block combines the alter-alter and alter-association ties, projecting the full PAN network.

2.4.1 Network Size Measures

Network size, or degree, signals how connected an individual is to their immediate social environment (Perry et al. 2018; Smith 2019). As Perry, Pescosolido, and Borgatti (2018) describe, degree (size) measures are used to indicate social integration, social activity, and potential for social support (Berkman and Glass 2000; McPherson et al. 2006). With typical ego network data, network size is operationalized as the total number of nominated alters, defined as the sum of discussion partners, for example. While many ego network studies truncate the number of nominations (usually limiting them to ten or fewer), typically to relieve respondent burden, network size remains a reliable measure enumerating how many people are core to an individual (Marsden 1993; McCarty et al. 1997; Perry et al. 2018). For the typical undirected structure of ego network data, network size is defined as the total number of nominated alters (N_d). Using the personal network in Table 2.4 (block 1) as an example, N_d can be calculated by summing either the number of rows or the number of columns of the adjacency matrix **X** corresponding to the personal network projection. This ego, for example, has a personal network degree (N_d) of five.

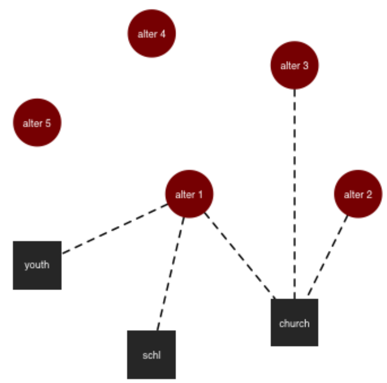
Table 2.4 Personal, Co-Membership, and Personal Affiliation Network Projections of a Toy Network

A. Personal Network
(only alter-alter ties)



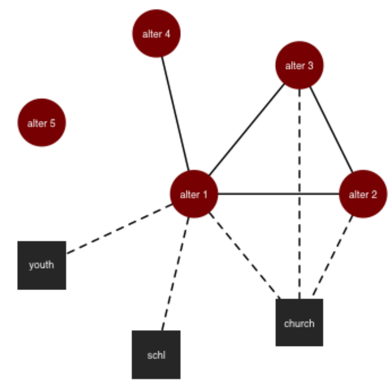
$$\boldsymbol{X} = \begin{array}{c} \\ alter_1 \\ alter_2 \\ alter_3 \\ alter_4 \\ alter_5 \end{array} \begin{array}{c} \begin{array}{ccccc} a_1 & a_2 & a_3 & a_4 & a_5 \end{array} \\ \begin{bmatrix} - & 1 & 1 & 1 & 0 \\ 1 & - & 1 & 0 & 0 \\ 1 & 1 & - & 0 & 0 \\ 1 & 0 & 0 & - & 0 \\ 0 & 0 & 0 & 0 & - \end{bmatrix} \end{array}$$

B. Co-Membership Network
(only alter-association ties)



$$\boldsymbol{A} = \begin{array}{c} \\ alter_1 \\ alter_2 \\ alter_3 \\ alter_4 \\ alter_5 \end{array} \begin{array}{c} \begin{array}{ccc} church & youth & schl \end{array} \\ \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \end{array}$$

C. Personal Affiliation Network
(alter-alter and alter-association ties)



$$\boldsymbol{P} = \begin{array}{c} \\ alter_1 \\ alter_2 \\ alter_3 \\ alter_4 \\ alter_5 \\ church \\ youth \\ schl \end{array} \begin{array}{c} \begin{array}{cccccccc} a_1 & a_2 & a_3 & a_4 & a_5 & chr. & yth. & schl \end{array} \\ \begin{bmatrix} - & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & - & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & - & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & - & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & - & - & - & - \\ 1 & 1 & 1 & 0 & - & - & - & - \\ 1 & 0 & 0 & 0 & - & - & - & - \\ 1 & 0 & 0 & 0 & - & - & - & - \end{bmatrix} \end{array}$$

● = Discussion Partner
■ = Voluntary Association
— = Alter-Alter Tie (discussion partner–discussion partner)
- - = Co-membership Tie (discussion partner–voluntary association)

Using a PAN data structure, two additional network size measures can be calculated: voluntary association degree and total personal affiliation network degree. It is important to decompose PAN degree into the number of personal ties and the number of associational ties because each may have its own important contributions to the individual. The size of an individual's voluntary association network is the total number of voluntary associations that an ego is connected to (N_v). Calculated in the same way as personal network degree, voluntary association degree is the sum of the voluntary association memberships of an ego. Using the affiliation matrix for the co-membership network (**A**; block 2 of Table 2.4), N_v is the total number of columns (3).

PAN degree, or the full network size, then, is the total number of personal and associational ties that an individual has. PAN network degree (N_p) is calculated by summing the personal network degree (N_d) and the voluntary association degree (N_v) (see Equation 2.1) or, equivalently, the sum of the rows or columns of the adjacency matrix (**P**).

$$PAN\ degree\ (N_p) = N_d + N_v \tag{2.1}$$

Table 2.5 presents a detailed summary of each measure introduced in this chapter. I rely on Table 2.5 was a way to distinguish the necessary data components and substantive contributions of each measure. The table is split by groups of measures from network size and network density to co-membership measures to measures of network cohesion. The general description, necessary data, example research question, and substantive contribution are detailed for each measure.

Table 2.5 Summary of All Proposed Measures Using a Personal Affiliation Network (PAN) Data Structure

Measures	Description	Data Needed	Example Research Question	Example Substantive Contribution
1. Network Size Measures	*Extent of social ties*			
Personal Network Degree	Total number of discussion partners	- Nominated alters	What is the spread of core network members of an ego?	- Social support - Social influence
Voluntary Association (VA) Degree	Total VA memberships of ego	- VA memberships	How integrated is an ego into society/their community?	- Social capital/resources - Civic engagement
PAN Degree	Total personal and VA ties of ego	- Nominated alters - VA memberships	What is the spread of an ego's personal network?	- Size of social environment - Social integration
2. Network Density Measures	*Network structure characteristic*			
Personal Network Density	Connectedness of personal ties	- Nominated alters - Alter-alter ties	How does support operate in low- and high-density personal networks?	- Social support - Information flow - Social integration
Co-membership Density	Rate of overlap between personal and associational	- Nominated alters - VA memberships - Alter-association ties	How densely coupled are alters and VA?	- Access to resources - Information flow
PAN Density	Connectedness of immediate social environment	- Nominated alters - VA memberships - Alter-alter ties - Alter-association ties	How do personal and associational, together, contribute to social integration?	- Social integration
3. Co-membership Measures	*Pattern of overlap*			
Any Co-membership	Indicator of co-membership in network	- Alter-association ties	Do PAN networks differ by co-membership?	- Shared contexts - Social boundaries
4. Proportional Composition	*Saliency of co-membership*			
Prop. Co-member	Saliency of co-members (alters)	- Nominated alters - Alter-association ties	How concentrated are co-members in core discussion networks?	- Social boundaries - Network composition

Prop. of VAs with Co-members	Saliency of co-membership within VAs	- Nominated alters - VA memberships - Alter-association ties	Is co-membership centered around a single VA or dispersed across VAs?	- VA membership concentration/composition
5. Magnitude of Co-membership	*Level/Rate of co-membership*			
Average Co-membership	Average number of co-memberships per alter	- Nominated alters - Alter-association ties	How embedded are alters in other dimensions of an individual's social environment?	- Social integration - Normative regulation
Average Co-members in VAs	Average number of co-members in VAs	- Nominated alters - VA memberships - Alter-association ties	What is the level of co-membership within VAs?	- Social resources - Associational turnover
6. Co-membership Concentration	*The variability in co-membership ties*			
Concentration of Co-membership	Variability of co-membership within alters	- Nominated alters - VA memberships - Alter-association ties	How diverse are co-members?	- Integration of personal and associational ties - Embeddedness of alters
Concentration of Alters in VAs	Variability of alters in VAs	- Nominated alters - VA memberships - Alter-association ties	To what extent are co-members concentrated in VAs?	- Diffusion potential - Level of embeddedness in VAs
7. PAN Cohesion	*Contextual measure of the connectivity of the network*			
Fraction in the Largest Component	Proportion of nodes connected by at least one path	- Nominated alters - VA memberships - Alter-alter ties - Alter-association ties	How cohesive (connected) are alters and voluntary associations?	- Minimal connectivity of full network - Spread of social support
Fraction in the Largest Bicomponent	Proportion of nodes connected by at least two independent paths	- Nominated alters - VA memberships - Alter-alter ties - Alter-association ties	How robust are PANs?	- Maximal connectivity of full network - Robustness of the network

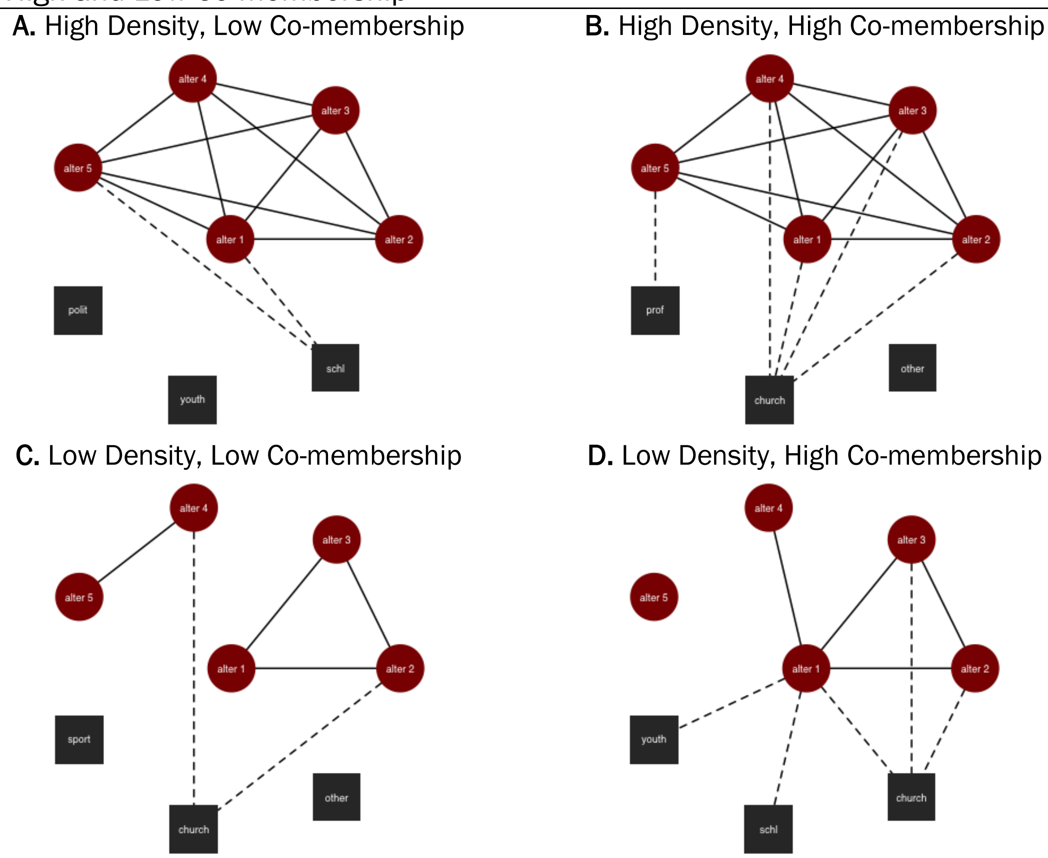
Personal network degree (N_d) and voluntary association degree (N_v) both inform how integrated an individual may be socially (through ties to close network members) as well as organizationally (through memberships in voluntary associations). Using Table 2.5 as a guide, a researcher could, for example, include the two measures separately in a model, each as its own predictor (see block 1; rows 1 and 2). The benefit to this approach is the ability to identify which space in a social environment is associated with a given outcome. What these measures miss, however, is the full spread of an individual's social environment, which may be particularly important given how social integration is conceptualized. PAN degree (N_p), as a summed measure, can be used to capture this spread (Table 2.5; row 3).

PAN degree details the total level of personal and associational connectedness that an individual has in their immediate social environment. Arguably, it is most similar to measures developed in previous studies, such as scales developed to measure general social connectedness (see Cornwell and Waite 2009, for example). However, PAN degree explicitly defines individual social connectedness as the total number of ties and not the combination of many factors, such as the number of ties, frequency of interaction, and aspects of social participation (Cornwell and Waite 2009).

2.4.2 Network Density Measures

Density, a key structural characteristic of an ego network (see block 2 in Table 2.5), measures how connected alters are within an ego's network (Perry et al. 2018; Wasserman and Faust 1994). Density can be used to assess social influence, social integration, and social cohesion. In general, denser networks have more connections among alters, and less dense networks have fewer ties. Network density can be used as an indicator of normative regulation and social influence, highlighting the connectivity of alters. Here, density can inform the personal, associational, and overall connections within a PAN data structure. Given the unique structure of PAN data, however, calculating density varies for each element. Below I detail three density measures, one for each element included in a PAN data structure: (1) personal network density (alter-alter ties), (2) co-membership density (alter-associational ties), and (3) PAN density (the combination of alter-alter and alter-association ties).

Figure 2.3 Example Personal Affiliation Networks (PAN) with High and Low Density by High and Low Co-membership



To further differentiate the measures in what follows, I present a 2x2 figure including four toy networks varying in personal network density and co-membership (see Figure 2.3). Each PAN network in Figure 3 has five nominated alters and three voluntary association memberships. Low personal network density is set at a value of 0.4 (where 40 percent of possible ties between alters are present) and high personal network density is set at a value of 1 (where every alter is connected). Additionally, the level of co-membership varies from low (two co-membership ties) to high (five co-membership ties). The toy network from Table 2.4 is the low-density, high co-membership example (network D). The other three networks in Figure 2.3 include network A, which has high personal network density and low co-membership; network B, which has high personal network density and high co-membership; and network C, which has low personal network density and low co-membership.

In a typical ego network context, density is defined as the number of ties among alters divided by the number of possible ties (Perry et al. 2018; Wasserman and Faust 1994). Here, all density measures are calculated without including the ego: the ego (node) and the ties between ego and alters are omitted. For typical ego network data measured by a single node type (e.g., discussion partners), density is limited to the possible connections between nominated alters. Density of a personal network (containing only alter-alter ties) can be calculated as the total number of ties between discussion partners (T_d) divided by the total possible ties between discussion partners (P_d) (see Equation 2.2). The total possible ties between discussion partners is N_d (N_d – 1)/2, where N_d is equal to the number of discussion partners nominated by an ego (i.e., personal network degree) (see Equation 2.2.1).

$$personal\ network\ density = \frac{T_d}{P_d} \tag{2.2}$$

$$P_d = \frac{N_d(N_d - 1)}{2} \tag{2.2.1}$$

The toy personal network (see Table 2.4) is loosely knit, with four of ten possible ties between alters present, so its personal network density is (4/((5(5-1))/2)), or 0.4.

While personal network density measures the connectedness of discussion partners within a given personal network, this does not adequately account for the other possible ties that exist within the context of a PAN data structure, such as co-membership ties (alter-association ties) and the combination of personal and association ties (alter-alter + alter-association ties). For example, in Figure 2.3, comparing the two high-density personal networks A and B (see the top row of Figure 2.3), the level of co-membership in the network has a direct impact on the structure of the network, where more co-membership ties produce a more integrated network. Furthermore, even for the loosely knit personal network (D), co-membership ties contribute more to the connectivity of the network than personal ties alone do.

Because the data structure of a personal affiliation network includes additional tie types beyond the typical alter-alter pairs, two additional density measures can be calculated. One measure is isolated to co-membership, and the other reflects the density of the full social environment captured with PAN data.

First, co-membership density, similar to personal network density, measures the connectedness of an ego's network. In this case, the connectedness is not between alters themselves, but rather between alters and voluntary associations. Rather than focusing on how alters are connected to each other, co-membership density looks at how much overlap exists between two different social contexts—discussion partners and voluntary associations. High co-membership density signifies a substantial amount of overlap between alters and voluntary associations, while lower co-membership density suggests that there are fewer ties (or less overlap) between alters and voluntary associations.

Calculating co-membership density uses the same logic as calculating personal network density, but it is limited to co-membership (alter-association) ties. To account for this isolation, the total possible ties are adjusted to reflect the total possible ties between alters and voluntary associations. Therefore, co-membership density is defined as the number of alter-association ties (i.e., co-membership; T_c) divided by the number of possible co-membership ties (P_c) (see Equation 2.3), where the number of total possible co-membership ties is equal to the number of discussion partners multiplied by the number of voluntary associations (N_d*N_v) (see Equation 2.3.1).

$$co - membership\ density = \frac{T_c}{P_c} \tag{2.3}$$

$$P_c = N_d * N_v \tag{2.3.1}$$

Using the co-membership network as an example (see Table 2.4), co-membership density can be calculated by taking the sum of affiliation matrix **A** divided by the number of rows (N_d) multiplied by the number of columns (N_v). Co-membership density, therefore is (5/(5*3)) or 0.33.

While co-membership density measures the connectivity between alters and voluntary associations, it does not take into account all elements of a PAN data structure. For example, only looking at co-membership density misses all personal connections that alters may have. Although co-membership density captures the rate of overlap between personal and associational spaces (see Table 2.5; block 2, row 2), it misses the connectivity of alters. Co-membership density may, in fact, be contingent on personal network density. That is, information flow and access to resources through organizations may be more likely in networks where alters are also tightly knit. This, however, cannot be explored without taking both alter-alter and alter-association ties into account. A PAN data structure has the possible ties *within* alters and *between* alters and voluntary associations and thus can account for the full PAN network structure (see Table 2.5; block 2, row 3).

Therefore, I construct an adjusted density measure to capture the density of PAN including all possible tie types.[3] Personal affiliation network density is defined as the sum of alter-alter and alter-association ties divided by the sum of total potential ties (see Equation 2.4). The PAN density of the example network is ((4 + 5)/(10 + 15)), or 0.36.

$$PAN\ Density = \frac{T_d + T_c}{P_d + P_c} \tag{2.4}$$

PAN density is important because it measures, to a fuller extent, how dense an individual's social environment is—accounting for overlap between alters and voluntary associations while also accounting for interpersonal ties (alter-alter ties). While previous research has identified various demographic correlates of personal

[3] Because association-association ties are not captured in a PAN data structure, and therefore are null, possible network ties are adjusted to calculate only possible ties between alters and between alters and organizations.

network density, other aspects, including the role of voluntary association membership, may influence the connectivity of personal networks. Take, for example, the tightly knit networks in Figure 2.3 (networks A and B). While both have all possible alter-alter ties, their co-membership densities vary quite dramatically. The co-membership density of network A, for example, is 0.13 whereas the density of the higher co-membership network (B) is 0.33—a 20 percentage point difference from the first network (A). While co-membership density would account for this difference, it does not consider both the personal and associational ties shaping network connectivity. In contrast, PAN density does take both into account. For both tightly knit personal networks (A and B; Figure 2.3), PAN density captures the difference between co-membership density by combining both personal connectivity and alter-association connectivity: the first network (A) has a PAN density of 0.48, and the second network has a PAN density of 0.60. Each of these networks would be treated as equally connected under typical ego network specifications (i.e., limited to alter-alter ties).

Although both the network size and network density measures are able to combine the personal and associational dimensions, some important distinctions are missed, particularly in regard to the patterning of alters in voluntary associations. To differentiate more detailed patterns of co-membership, I introduce additional measures in the following section that focus on co-membership ties specifically.

2.4.3 Co-membership Measures

The use of co-membership in previous research, where it was typically limited to a single type of relation (i.e., “co-member”; see McPherson et al. 2006), cannot capture important granularities about co-membership ties. Specifically, when isolated to a single relation type, co-membership neither captures details about how alters are distributed across organizations nor measures the number of co-memberships a given alter has. This next set of measures focuses on the ties between alters and associations. Each co-membership-specific measure better identifies patterns of overlap between personal and associational ties.

Because the level of connectivity in PAN varies between cases when there is overlap between alters and associations and cases when there is no overlap, I first create an indicator for co-membership. Then, I introduce an additional set of measures to differentiate patterns of overlap. Each co-membership-specific measure relies on summary measures that, when aggregated, can differentiate patterns in co-membership across a sample of egos. Given that the co-membership-specific measures connect the personal and associational, each measure can be defined by using a co-membership affiliation adjacency matrix (**A**) (see Table 2.4) focusing on co-membership (alter-association ties) alone.

2.4.3.1 Any Co-membership

Any co-membership is a dichotomous indicator that captures if an ego network has any overlap between personal and associational networks. On its own, any co-membership does not capture information about the level or concentration of overlap. For example, it does not indicate whether specific organizations have more overlap than others, nor does it indicate whether co-membership is dispersed across alters or, alternatively, only one alter is a co-member. Rather, any co-membership can be used to differentiate ego networks, separating those that have overlap from those that do not. As a point of comparison, any co-membership, at a basic level, can provide information about the likelihood that core network members are also involved in other shared contexts, such as voluntary associations.

Defined as a Boolean indicator where “1” indicates co-membership and “0” indicates no co-membership, any co-membership can be derived using the co-membership affiliation matrix (**A**) for each ego (see Table 2.2, for example). In Equation 2.5, any co-membership is defined as “0” if the sum of **A** equals 0 and “1” if the sum of **A** is greater than or equal to 1.

$$\mathit{Any\ Co\text{-}membership} = \begin{cases} 0, if \sum \mathbf{A} = 0 \\ 1, if \sum \mathbf{A} \geq 1 \end{cases} \tag{2.5}$$

Taking the toy network in Table 2.4 as an example, co-membership can be calculated using the co-membership affiliation matrix (**A**). The total sum of co-membership ties is 5, and therefore the co-membership indicator is “1.” Additionally, each network in Figure 2.3 has the same value for the co-membership indicator (1). When looking at the figure, however, it is evident that the binary indicator misses important distinctions between low and high levels of co-membership. Moreover, the indicator alone cannot identify whether co-membership is isolated to a single alter or distributed across alters. To account for these shortcomings, other common measures can be used to gauge the graph-level summary of co-memberships and disentangle the distribution of co-membership across both alters and voluntary associations. Two measures can be used to estimate the composition of co-membership with PAN—one focusing on co-membership of alters and one focusing on co-membership within voluntary associations.

2.4.3.2 Co-membership Measures: Proportional Composition

2.4.3.2.1 Proportion Co-member

Proportion co-member, like other proportional variables (e.g., proportion female, proportion kin) captures the compositional structure of an ego network (Perry et al. 2018). Here, proportion co-member is a measure that gauges the relative percentage of alters who are co-members within an ego's PAN. Proportion co-member is defined as the ratio of co-members (N_{dc}/N_d; see Equation 2.6), where N_{dc} is the number of alters who are co-members and N_d is the total number of discussion partners nominated.

$$Proportion\ Co\text{-}member\ =\frac{N_{dc}}{N_d} \tag{2.6}$$

Determining the proportion of co-members in a given network can be demonstrated using the network plot (B) in Table 2.4. The toy co-membership network contains five alters and three voluntary associations in which three of the alters are co-members. Therefore, the proportion co-member is 0.6 (3/5), which can be used to explore the extent of overlap between an individual's alters and voluntary association memberships. The proportion of co-membership in a PAN can inform research related to social boundaries and network composition and answer questions related to the concentration of co-members in core discussion networks (see Table 2.5, block 4 for examples).

In Figure 2.3, both the high-density, low co-membership and low-density, low co-membership networks (A and C) have 40% of alters who are co-members (2/5). In the high-density, high co-membership network (B), every alter is a member of at least one organization. The proportion co-member measure, however, cannot identify how concentrated co-memberships are within voluntary associations. For example, the proportion of alters who are co-members does not identify whether several of an ego's voluntary association(s) have at least one co-member or whether co-membership is isolated to a single association.

2.4.3.2.2 Proportion of Associations with Co-Members

To explore the concentration of co-membership within voluntary associations themselves, the second compositional measure focuses on voluntary associations. Rather than summarizing the relative co-membership of core network members, researchers may want to identify how co-membership operates within associations (see Table 2.5, block 4). Co-membership in voluntary associations, therefore, can be captured by a proportional measure focusing on an ego's voluntary association memberships. The proportion of voluntary associations with co-members is a measure capturing the fraction of associations that have alters as co-members and is defined as a ratio of voluntary associations with co-members to the total number of voluntary association memberships (N_{vc}/N_v; see Equation 2.7).

$$Proportion\ of\ VA\ with\ Co\text{-}members\ =\ \frac{N_{vc}}{N_v} \qquad (2.7)$$

N_{vc} is the number of voluntary associations with co-members, and N_v is the total number of voluntary associations of which the ego is a member. Using the same toy network (Table 2.4, network B), the proportion of voluntary associations with co-members is 1 (3/3) when all associations have at least one co-member. The proportion of associations with co-members can identify how salient co-membership is across associations. Looking at Figure 2.3, it is evident that co-membership in voluntary associations varies from network to network. For networks A and C, only one-third of the ego's voluntary associations have shared members, whereas the majority (0.67) of network B's associations have co-members and all of network D's associations have co-members.

While both proportional measures capture the composition of co-membership for alters and associations, they are still limited. Specifically, the proportional measures isolate co-membership to a single relation and cannot capture the level of co-membership, whether of a given alter or within an association. For instance, in the low-density, high co-membership network (D) in Figure 2.3 "alter 1" is not differentiated from the other two alters with co-membership ties. The proportion of co-membership measure does not account for the three co-membership ties of alter 1 in relation to the single co-membership ties of alters 2 and 3. Similarly, the proportion of co-members in voluntary associations measure equates the level of co-membership in youth and school groups to the level of co-membership in church, though the level of co-membership in church is three times that in the other two organizations. Given that a researcher may be interested not only in the composition of co-membership but also the level of embeddedness of alters and voluntary associations, additional measures are needed.

The data structure of PAN can be used to extract more detailed information about the level and concentration of co-membership within an individual's social environment. To retain both the multiple co-membership ties a given alter may have and the variability of co-membership ties across organizations, I construct two additional sets of measures. The first set captures the magnitude of co-membership, and the second set captures the concentration of co-membership. I detail each measure's construction, focusing on a specific node type—alters or voluntary associations.

2.4.3.3 Co-membership Measures: Magnitude of Co-membership[4]

To better measure the relative structure of co-membership using sampled ego network data, I construct two measures to account for the multiple co-membership ties between multiple alters and multiple associations. Like above, each can focus on one node type, depending on the point of interest. For example, one could ask about the extent to which alters are embedded within other spaces of an individual's social environment (e.g., how many organizations do alters tend to be co-members of? See Table 2.5, block 5). On the other hand, one many need to know the level of co-membership within voluntary associations (e.g., do organizations tend to have many co-members or not? See Table 2.5, block 5).

2.4.3.3.1 Average Co-membership

Average co-membership of alters is a measure that captures the level (or magnitude) of overlap between alters and voluntary associations, with a focus on alters. Average co-membership measures the number of associations in which an alter is a co-member within a given PAN network. This alter average can be defined by taking the total sum of co-membership ties (T_c; defined in Equation 2.8) divided by personal network degree (N_d) (see Equation 2.8.1), where T_c can be derived by taking the sum of the co-membership affiliation matrix (**A**).

[4] Both average measures depend on the size of both personal and affiliation degree.

$$Average\ Co - membership\ (alters) = \frac{T_c}{N_d} \tag{2.8}$$

$$T_c = \sum \boldsymbol{A} \tag{2.8.1}$$

Using the toy network (see Table 2.4), average co-membership is 1 (5/5). This can be interpreted to mean that, on average, an alter is a co-member of one association with the ego. Average co-membership, on its own, provides more information about how embedded core network members are in the organizational dimension of an individual's social environment. An average higher than 1 would suggest that, relative to the number of alters nominated, those with whom an ego discusses important matters tend to be embedded in other dimensions of that ego's social environment. An average lower than 1 would suggest that co-members are less embedded in the organizational dimension of an ego's social environment.

Comparing network A to network B in Figure 2.3 highlights the varying levels of co-membership across alters. The high-density, low co-membership network (A) has, on average, 0.40 co-memberships per alter, whereas the high-density, high co-membership network (B) has 1 co-membership per alter, on average. The overall level of co-membership for alters is higher in network B than in network A. One drawback of the average co-membership of alters measure, however, is its inability to identify the level of co-membership within associations.

2.4.3.3.2 Average Co-members in Associations

Alternatively, we could measure the average level of co-membership within voluntary associations. Here, the average number of co-members is an association-specific measure capturing the level of co-membership within associations. It is defined as the total co-membership ties (T_c) divided by voluntary association degree (N_v) (see Equation 2.9).

$$Average\ Co-members\ (VA) = \frac{T_c}{N_v} \tag{2.9}$$

The average co-members in associations for the toy network in Figure 2.4 is 1.67 (5/3), which means that, on average, there are 1.67 co-members in each of the voluntary associations of which the ego is also a member. In other words, there is a higher level of co-membership within voluntary organizations relative to the co-membership level of alters. These distinctions are meaningful when considering the embeddedness of personal and associational dimensions when considering social integration, normative regulation, social resources more generally (see Table 2.5, block 5).

Having averages of less than 1 for both co-memberships per alter and co-memberships per voluntary association suggests that an individual's core network members and their social participation are relatively separate from each other (i.e., the personal and associational spaces in their social environment are not integrated). This is evident in both of the low co-membership networks in Figure 2.3 (networks A and C). Both networks have an average of 0.4 co-memberships per alter and 0.67 co-memberships per voluntary associations. That is, even with varying levels of connectedness within their personal networks, neither A nor B have high levels of overlap between their personal and associational social environments, except for select alters and a single organization.

Both of the magnitude measures above are able to gauge the rate of co-membership for both alters and voluntary associations. In contrast to co-membership density, which estimates the expected chance of an alter being a co-member or an association having a co-member, these two measures can evaluate the extent of overlap between personal and associational environments. Average co-membership, for example, allows researchers to explore the embeddedness of alters in other spaces of an individual's social environment, which is important for understanding social integration and normative regulation (see Table 2.5, block 5). One could ask, for example, about the number of organizations in which alters tend to participate. Conversely, the average co-membership in voluntary associations can be used to explore questions related to associational turnover and the types of social resources organizations provide. Additionally, average co-membership in voluntary associations can be used to identify whether organizations tend to have many co-members or isolated co-membership.

While helpful for assessing the rates of co-membership, these magnitude measures are limited. Neither measure can identify how concentrated overlap is between alters and associations. For example, calculating the average number of co-members in an association cannot differentiate whether one alter is in every one of an ego's organizations or whether there is a separate alter in each organization. Additionally, the average co-memberships of alters cannot differentiate whether co-membership is specific to a single alter or co-membership is spread across alters.

To better assess the concentration of co-membership, I construct two measures that capture the variability of co-memberships—one specific to alters and one specific to voluntary associations. Both concentration measures are based on the variance of co-membership ties, where lower values suggest low variability (relatively distributed alter-association ties) and higher values suggest the concentration of co-membership ties within one alter or one voluntary association.

2.4.3.4 Co-membership Measures: Co-membership Concentration

2.4.3.4.1 Concentration of Co-membership

Concentration of co-membership identifies the amount of variability in the number of co-memberships each alter has (i.e., the number of alter-association ties per alter). Researchers can use this concentration measure to explore the diversity and types of co-members that an ego has (see Table 2.5, block 6). Defined as the variance of alter co-membership, concentration of co-membership can be calculated by taking the variance of the co-membership affiliation matrix (**A**) row sum vector ($\mathbf{x_d}$) (see Equation 2.10), where $\mathbf{x_d}$ is a d-by-1 vector, totaling the number of co-membership ties (alter-association ties) that each alter has.

$$concentration\ of\ co-membership = var(\boldsymbol{x_d}) \qquad (2.10)$$

$$var(\boldsymbol{x_d}) = \frac{\sum_{i=1}^{N_d}(\boldsymbol{x_{di}} - \overline{\boldsymbol{x_d}})^2}{N_d - 1} \qquad (2.10.1)$$

For the co-membership network (B) in Table 4, $\mathbf{x_d}$ = {3,1,1,0,0} and the concentration of co-membership is 1.5 (6/4). A value of “0” for the concentration of co-membership is interpreted as an equal distribution of co-membership across alters. This “0” variability is demonstrated in Figure 2.3, network B, in which each alter has a single co-membership tie. When comparing the co-membership concentration of network B to that of network D, it is evident that in network D, co-membership is highly concentrated for one alter (alter 1), which has 60% of the co-membership ties. This distinction is only highlighted through the concentration measure, as both network B and D have the same values of average co-membership and average co-members in voluntary associations. Additionally, even at low levels of co-membership, the concentration of co-membership can differentiate the spread of the co-membership ties, as seen in network A in Figure 2.3, in which each of the two co-membership ties is spread across two alters. The concentration of co-membership is 0.30, suggesting some variability as the majority of alters have no co-membership ties, but of those that do, the co-membership is split evenly.

Each of the co-membership specific measures is limited to a single focal dimension, and the concentration of co-membership measure is no different. The concentration of co-membership, while informative for researchers focusing on the embeddedness of specific alters (see Table 2.5, block 6), cannot simultaneously capture how concentrated co-memberships are across organizations. To capture the organizational concentration, I define the concentration of alters in voluntary associations below.

2.4.3.4.2 Concentration of Alters in Voluntary Associations

The concentration of alters in voluntary associations is similar to the concentration of co-membership in capturing the variability of co-membership, except here the concentration is focused on voluntary associations. Rather than highlighting co-membership of alters, the concentration of alters in voluntary associations indicates whether all co-memberships are housed in one association (e.g., church) or are dispersed across organizations (e.g., book club, sports team, and political group). Researchers could, for example, use this measure to identify whether one organization has more influence than another. Additionally, understanding whether normative regulation is centralized in one organization or spread across many can inform individual outcomes related to strain, well-being, and the like when exploring the potential for diffusion within a network (see Table 2.5, block 6).

Defined as the variability in the number of alters who are co-members in an ego's voluntary associations, the concentration of alters in voluntary associations can be calculated by taking the variance of the co-membership affiliation matrix (**A**) column vector ($\mathbf{x}_v$) (see Equation 2.11), where $\mathbf{x}_v$ is a 1-by-v vector, totaling the number of co-membership ties in each voluntary association.

$$concentration\ of\ alters\ in\ VA = \ var(\boldsymbol{x}_v) \tag{2.11}$$

$$var(\boldsymbol{x}_v) = \frac{\sum_{i=1}^{N_v}(\boldsymbol{x}_{vi} - \overline{\boldsymbol{x}_v}\,)^2}{N_v - 1} \tag{2.11.1}$$

The concentration of alters in voluntary associations for the toy network (Table 2.4) is 1.33, where $\mathbf{x}_v$ = {3,1,1}. There is relatively moderate variability in the number of co-members in voluntary associations, where church has 60% of the co-membership ties and the other two associations each have a 20% share of ties. When we compare the toy network (also network D in Figure 2.3) to other similar networks, we can see that variability is an important measure to capture the spread of co-memberships in associations. For example, let's compare network D to network B, both of which have the same number of co-membership ties (5). The concentration of alters in associations is 1.33 for network D but 4.33 for network B. Network B has a higher level of co-membership concentration in a single organization than the other high co-membership network (D), where 80% of all co-membership ties are within one organization—church.

Each of the co-membership measures detailed above extends traditional summary network measures by linking personal and associational ties. While each helps explain the ways in which personal and associational spaces are tied together, none incorporate alter-alter ties and alter-association ties concurrently. To better account for the dependent structure of PAN, I introduce two final measures featuring both alter-alter and alter-association ties that capture the cohesiveness of personal affiliation networks.

2.4.4 PAN Cohesion

In an attempt to retain both ties between alters and ties between alters and voluntary associations in a single measure, I use two measures that capture component size and bicomponent size, two measures used to understand the overall cohesiveness of a network. Component size captures the minimal cohesion in a network, whereas bicomponent size captures the maximal level of cohesion within a network (Moody and White 2003). Both PAN cohesion measures are contextual, capturing how robust (or embedded) the structure of the network is. The more cohesive an individual's social environment, the more robust the network is and the less it is influenced by the loss of any given node. Substantively, PAN cohesion can identify the integrative and regulatory nature of an individual's social environment (see Table 2.5, block 7). The benefit of these cohesion measures, especially when using a PAN data structure, is their ability to focus on the overall tie structure. Both of the measures, therefore, incorporate both alter-alter and alter-association ties.

The first PAN cohesion measure—fraction in the largest component—defines the component of a network as the maximal set of nodes that can be reached by at least one path (Moody and White 2003). Used as a measure of minimal cohesion, the fraction in the largest component captures which nodes can reach each other at all. Because the measure requires only a single path between nodes, when a single node is removed, the network may be subject to fragmentation.

Defined as the proportion of nodes in the largest component of the graph, the fraction in the largest component, therefore, can be calculated as the ratio of nodes (alters and associations) in the largest component (N_{comp}) divided by the number of nodes in the PAN (i.e., PAN degree (N_p)) (see Equation 2.12), where N_{comp} is the largest element in the $\mathbf{x_{comp}}$ vector (see Equation 2.12.1). $\mathbf{x_{comp}}$ is a n-by-1 vector, where the length of the vector is equal to the number of components in PAN network *l*, with values representing the number of nodes in each component. The most cohesive networks, therefore, have a value of "1"—where every alter and association is connected. The minimum value of "0" indicates that none of the nodes—neither alters nor associations—are connected.

$$fraction\ in\ the\ largest\ component\ = \frac{N_{comp}}{N_p} \tag{2.12}$$

$$N_{comp} = \max(\boldsymbol{x_{comp}}) \tag{2.12.1}$$

The personal affiliation network (PAN) in Table 2.4 has two components. One component is made up of seven nodes (four alters and three voluntary associations), and the other is an isolated alter where $\mathbf{x_{comp}}$ = {7,1}. The toy PAN network, therefore, has 88% (7/8) of nodes (both alters and voluntary associations) in the largest component.

One limit to the component measure, however, is its minimal measurement of cohesion. Because a component is defined as a minimal level of cohesion (requiring only a single unique path), if a single alter ties together much of the network, its removal would fragment the network structure. Take, for example, alter 1 in the toy network (Table 2.4 and Figure 2.3, network D). If alter 1 were removed from the network, the network would lose almost all cohesiveness, as alter 1 links many nodes in the network together. The fraction in the largest component is a good summary measure for the general cohesiveness of a PAN but is limited if a researcher wants to understand the level of embeddedness within the network.

The second PAN cohesion network—fraction in the largest bicomponent—is a more stringent measure of cohesion, allowing a researcher to better assess the embeddedness of the network. The fraction in the largest bicomponent is defined as the maximal number of nodes reached by at least two independent paths (Moody and White 2003). As a result, it is more robust to disconnection. If an ego were to leave a voluntary association, for example, but their co-member was connected to another association or to at least one other alter, the structure of the network would be minimally impacted. A strongly cohesive PAN will provide individual egos a sense of community and the potential for greater social support, as their friends are also members of organizations and are more generally connected.

The fraction in the largest bicomponent is defined as the ratio of nodes (alters and associations) in the largest bicomponent (N_{bicomp}) divided by the number of nodes in the PAN (i.e., PAN degree (N_p)) (see Equation 2.13), where N_{bicomp} is the largest element in the $\mathbf{x}_{bicomp}$ vector (see Equation 2.13.1). $\mathbf{X}_{bicomp}$ is a n-by-1 vector, with a length equal to the number of biconnected components in PAN network *I*, with values representing the number of nodes in each biconnected component. As in the first PAN cohesion measure, the value can range from 0 to 1. With the bicomponent measure, however, the most cohesive PAN networks (with a value of “1”) are characterized by at least two independent paths tying together every alter and association.

$$fraction\ in\ the\ largest\ bicomponent = \frac{N_{bicomp}}{N_p} \tag{2.13}$$

$$N_{bicomp} = \max(\boldsymbol{x_{bicomp}}) \tag{2.13.1}$$

The toy network in Table 2.4 has four components, where four nodes (alter 1, alter 2, alter 3, and church) are in the largest biconnected component. The max($\mathbf{x}_{bicomp}$), therefore is equal to 4, where 50% (4/8) of nodes are in the largest bicomponent of the PAN.

The fraction in the largest bicomponent is a particularly useful measure when comparing different network structures that may have many unique patterns of co-membership and personal ties. Take, for example, the two high-density networks in Figure 2.3 (networks B and D). Both networks, while varying in personal network density, have the same fraction of nodes in the largest component. However, using the more stringent measure of cohesion, one can see that network D is subject to more fragmentation than network B.

Additionally, the biconnected component measure can identify seemingly disparate networks that, in fact, have similar cohesive clusters. The two high-density networks in Figure 2.3 (networks A and B), for example, vary in their level of co-membership, but their maximal cohesion is quite similar, as both have 75% of their nodes in the largest biconnected component. The fraction in the largest bicomponent, therefore, is an ideal measure for assessing the integrative and robustness of a PAN by combining both alters and associations.

2.5 CONCLUSION

This chapter offers a new framework for measuring social integration for sampled ego networks. Standard ego network data use only a single node type when exploring the core networks of individuals (Bernard et al. 1990; Marsden 1987; Perry et al. 2018). This siloed focus on a single node type, however, does not account for other dependencies and ties that individuals have to other spaces in their immediate social environments. The proposed method directly measures two spaces of an individual's social environment as a way to better measure the social integration of individuals.

Combining personal and associational spaces of an individual's social environment, personal affiliation networks (PAN) extend the traditional ego network data structure to incorporate multiple node and tie types. Personal networks have historically been used as a window into an individual's social world (Perry et al. 2018), and they operate as integrating and regulatory spaces (Berkman et al. 2000; McPherson et al. 2006; Smith et al. 2014; Verdery and Campbell 2019). Voluntary associations have similar regulatory and integrative properties that connect individuals to a set of collective events (Bonikowski and McPherson 2007; Booth and Babchuk 1969). Those people who are core to our networks, however, may also be members of the same voluntary associations. Little research has connected the personal and association networks of individuals (Cornwell and Waite 2009; Davis et al. 2006; Mollenhorst 2008; Mollenhorst et al. 2012), and no research has directly measured the connection between alters and between alters and associations directly.

This chapter outlined a potential data structure and corresponding measures that can better measure social integration by linking personal networks and voluntary associations. Using an extended network structure (PAN), I developed modified network measures to map the overlap and dependencies between personal networks and voluntary associations directly. Each of the measures described in this chapter can be used to capture more detailed information about the immediate social environment of an individual. Depending on the focus and research question at hand, some measures may work better than others. The chapter that follows uses data with a PAN data structure as a case study. I first explore the distribution of the measures developed in this chapter and then explore the relationship between each measure and ego-level characteristics.

CHAPTER 3 WHO IS SOCIALLY INTEGRATED? AN APPLICATION OF PERSONAL AFFILIATION NETWORKS USING THE 2006 NVAS

3.1 INTRODUCTION

Social integration has been a fundamental concept linking individuals to society through interpersonal relationships, groups, organizations, and formal institutions (Berkman and Glass 2000; Durkheim 1951; Pescosolido and Rubin 2000). The structure of an individual's social environment has a direct influence on their well-being, from health outcomes to social support (Berkman and Glass 2000; Seeman 1996). Interpersonal and collective ties shape social integration and normative regulation, influencing one's identity and available resources (Marsden and Friedkin 1993; McPherson et al. 2006). Personal (ego) networks have been used as a window into an individual's immediate social environment. More densely connected and supportive networks can provide support for individuals in times of need (Berkman and Glass 2000; Campbell and Lee 1992; Perry et al. 2018). Being integrated into a community provides further benefits (Campbell and Lee 1992; Cornwell and Dokshin 2014; Seeman 1996). Specifically, voluntary associations tie individuals to social groups and provide exposure and access to a broader set of emotional and financial resources (Bonikowski and McPherson 2007; Kim 2016; McPherson and Rotolo 1995).

Scholars have explored the structure and composition of personal networks, using ego network measures as a proxy for social integration (Giannella and Fischer 2016; Perry et al. 2018; Smith 2019; Vacca 2019). Both structural and compositional measures operate as important indicators for predicting individual outcomes, including from physical and mental health, identity formation, and socioeconomic mobility (Berkman and Glass 2000; Ho 2016). What we know about individual social integration is largely based on interpersonal ties between an individual (ego) and their close personal contacts (alters) (Marsden 1987; McPherson et al. 2006; Perry et al. 2018). Although studies have theorized many ways that individuals are tied to social environments, such as the duality of persons and groups, concentric social circles, and social foci (Breiger 1974; Feld 1981; Simmel 1955), research has yet to measure social integration in a manner that incorporates both personal and associational ties. Those alters that are core to an individual's personal network may also be members of the same voluntary associations as the ego. To date, however, research has largely omitted such connections and thus cannot fully capture the extent of individual social integration. The way that alters may shape and structure individual networks, above and beyond personal ties alone, has yet to be explored systematically.

In addition to previous discoveries about network structure and composition, research has identified demographic correlates associated with the same personal network measures, identifying who is more (or less) likely to be socially integrated (McPherson et al. 2006). Past work has also used ego network measures as the outcome of interest, asking how individual characteristics, such as race or gender, predict ego network structure and composition (McPherson et al. 2006). For example, the personal networks of men have been identified as more diverse and less kin-centered than the personal networks of women (Marsden 1987; McPherson et al. 2006; Moore 1990),[5] black people and other racial minorities have been identified as having smaller networks than their white counterparts (Marsden 1987; McPherson et al. 2006), and younger and more educated individuals have been identified as having more diverse networks than older and less educated individuals (Marsden 1987; McPherson et al. 2006; Munch, McPherson, and Smith-Lovin 1997). These differences in network structure help explain some of disparities in health, social support, and general well-being (Berkman and Glass 2000; Campbell and Lee 1992; Seeman 1996; Verdery and Campbell 2019). However, they focus only on the role of personal ties and do not precisely enough link social connections to other social settings, such as voluntary associations.

There is a largely separate literature that has found differences in voluntary association participation across demographic groups. For example, outside of religious communities, women and men often participate differentially in the associations they belong to, as in the case of gender-segregated sports groups (Curtis, Grabb, and Baer 1992; McPherson and Smith-Lovin 1982, 1987). Additionally, individuals with higher education and income levels tend to participate in a broader, more diverse set of associations (Curtis et al. 1992; Sandstrom and Alper 2019), and individuals who are affiliated with religious communities tend to participate in other voluntary associations at higher rates than those who are not religiously affiliated (Cnaan et al. 2003; Schwadel 2011; Taylor and Chatters 1988). Research identifying differences in voluntary association participation may illuminate

[5] However, gender differences in personal networks vary over time; women, for example, have an increasing number of connections to the world outside of family.

differences in the associations themselves, such as the demographics of their members and the resources they can provide to those members.

Extant research cannot identify the multiple types of social connections in an individual's social environment, nor can it properly identify how actors are intertwined with each other. As a result, the research misses key aspects of social life, as people's personal and associational ties do not operate in isolation. Moreover, because previous research has used simple measures specific to either personal or associational ties, it cannot fully capture differences in network structure across demographic groups.

Several important questions remain about how personal and associational ties come together in personal networks. The key question here is whether incorporating both associational and personal ties into measures of ego network structure challenges our current understanding of integration across demographic groups. This can only be answered by developing better measures for social integration that incorporate both personal and associational ties. Therefore, the following chapter is concerned with addressing two main research questions: (1) How do we measure social integration when using both personal and associational ties? (2) How do these structural and compositional measures vary across individuals?

This chapter takes up these questions directly by linking personal ties to the associational memberships of individuals and exploring the distribution of PAN structural measures (defined in Chapter 2) across individuals. Relying on the personal affiliation network (PAN) data structure and corresponding measures presented in the previous chapter, I use the 2006 National Voluntary Association Study (NVAS) as a case study to assess the structure and composition of sampled ego networks. The NVAS includes detailed ego network and co-membership network data that can be combined to create the PAN data structure necessary to capture personal and associational ties simultaneously.

I begin with a short background on the known individual demographic correlates of personal network structure and composition (Section 3.2.1), participation in voluntary associations (Section 3.2.2), and detail the current study (Section 3.2.3). Next, using previous research on network structure, network composition, and social integration, I present a set of hypotheses outlining the expected findings (Section 3.2.4). I then describe the 2006 National Voluntary Association Survey data (Section 3.3), detailing key features of the survey used to measure the necessary PAN data structure (Section 3.3.1). Following the methods of analysis (Section 3.3.2), I present two sets of findings focusing on the chapter's two main research questions (Section 3.4). First, I focus on the PAN measures themselves, describing their distribution (i.e., size, density, co-membership, and cohesion) and their relationship to each other (Section 3.4.1). Second, by switching the focus to individuals (i.e., egos), I explore how patterns of social integration vary across demographic groups for each PAN measure (Section 3.4.2). I conclude by discussing the findings and suggesting avenues for future research utilizing a PAN data structure and corresponding measures (Section 3.5).

3.2 BACKGROUND

Researchers have examined both personal networks and participation in voluntary associations to understand individual social integration. Both personal network structure and composition and voluntary association participation provide insights into an individual's personally and associative ties. Using these ties, researchers can better understand the benefits associated with being socially integrated.

3.2.1 Ego Characteristics and Personal Network Structure

The extensive existing literature on personal networks has focused on two applications. First, researchers have used the structural and compositional makeup of personal networks to predict individual-level outcomes (Berkman 2000; Binder et al. 2012; Campbell and Lee 1992; Fischer 1982), including health and well-being, social support, social isolation, and social influence (Ho 2016; Marsden and Friedkin 1993; Perry et al. 2018; Seeman 1996; Verdery and Campbell 2019). For example, larger and denser networks have been associated with higher levels of social support, better health outcomes, and decreased loneliness (Campbell and Lee 1992; Cornwell and Waite 2009; Ho 2016; Seeman 1996). Similarly, compositional measures such as tie characteristics or tie strength are linked to self-rated health and resource mobilization in times of need (Agneessens et al. 2006; Campbell and Lee 1992; Fiorillo and Sabatini 2011). Second, researchers have used features of personal networks as outcomes. Specifically, researchers have used ego-level characteristics to identify key distinctions in the structure and composition of networks across individuals (Marsden 1987; McPherson et al. 2006; McPherson, Smith-Lovin, and Cook 2001; Smith et al. 2014).

Sociodemographic indicators such as gender, race, education, and income have been widely used by researchers when identifying differences between personal networks (Marsden 1987; McPherson et al. 2006; Moore 1990; Roberts et al. 2008). For example, men are more likely to be socially isolated than women (McPherson et al. 2006). Further, women tend to be emotionally closer to their family members—receiving more social support from their family relationships than men (Verdery and Campbell 2019). Historically, women tend to have networks that are more kin centered, and their kin networks are denser (Marsden 1987; McPherson et al. 2006). While this had been attributed to men's greater access to a more diverse set of networks—because men were more likely to have connections across multiple social settings (e.g., the workplace), women now have more opportunities for creating and maintaining connections to their broader social environment. However, gender remains an important indicator for predicting social network structure and composition (Marsden 1987; McPherson et al. 2006; Mennis and Mason 2012; Roberts et al. 2008; Smith-Lovin and McPherson 1993).

Other demographic characteristics have also been found to influence personal network structure and composition. Previous research, for example, has identified that more highly educated individuals and those with larger incomes tend to have networks that are less kin centered, more diverse, and less dense (McPherson et al. 2006). Here, an increased variety of opportunities and greater access to resources are expressed through a more diverse set of connections: those who have more personal resources themselves are able to access more resources embedded in personal relationships (Verdery and Campbell 2019). Age also shapes social networks. For example, the personal networks of older adults rise until middle age, then begin to decline, as does their social activity (Smith et al. 2015). Lastly, research has identified a consistent pattern of black and other nonwhite individuals having smaller, denser networks compared to their white counterparts (McPherson et al. 2006). Taken together, this literature justifies further research identifying whether these same disparities hold when focusing on more nuanced measures of social integration beyond personal network characteristics, thus offering new, more contextualized understandings of previous findings.

3.2.2 Ego Characteristics and Voluntary Association Participation

Researchers also use voluntary associations as another context for quantifying social integration. Voluntary associations, which serve both expressive and instrumental purposes (Booth and Babchuk 1969), bind individuals to collective events and maintain and reinforce values, institutions, and practices (Bonikowski and McPherson 2007; Rotolo 1999; Wellman and Wortley 1990). According to some studies, voluntary associations operate as an integrating space, providing access to a broader, more diverse set of resources (Bekkers 2005; Pescosolido and Rubin 2000; Popielarz and McPherson 1995; Putnam 2000a; Wellman 2000). Others, however, argue that voluntary associations draw similar, rather than diverse members, promoting homophily (McPherson and Rotolo 1995; Popielarz 1999c, 1999b; Popielarz and McPherson 1995). If this is the case, individuals may not benefit from the hypothesized integrating returns of association membership. Instead, voluntary associations may be detrimental to social connectivity by promoting redundant ties.

Researchers focusing on individual-level memberships have asked two primary questions: (1) who joins voluntary associations, and (2) what are the consequences of these memberships? More recently, because of shifts in civic participation, researchers have become increasingly concerned with the first question (Cnaan et al. 2003; Paxton 1999; Putnam 2000a; Rotolo 1999). Accordingly, studies have relied on individual-level correlates to predict the type and number of voluntary association memberships individuals may have (Curtis et al.

1992; Davis et al. 2006; Horowitz 2015; Kim 2016; Knoke and Thomson 1977; Mollenhorst 2009) and how other associative habits may influence social participation. Previous studies, for example, have found that church-affiliated individuals are more likely than those who are not church-affiliated to be members of other associations (Kim 2016; Osborne, Ziersch, and Baum 2008; Rap and Paxton 2018; Rotolo 1999).

In addition to religious affiliations, other demographic correlates are associated with individual voluntary association participation. For example, a curvilinear pattern in individual membership associated with age has been identified (Cutler and Hendricks 2000; Knoke and Thomson 1977; Rotolo 1999). Rotolo (1999) notes that the number of memberships peak among middle-age adults and are lower among younger and older populations. However, age differences may instead be related to broader associative habits of individuals over time. For example, McFarland and Thomas (2006) identify the lasting impact on participation in young adults, where early association participation is maintained over time. Individual characteristics associated with social capital and network connectivity such as socioeconomic status and education are also known to contribute to voluntary association memberships, with higher levels of education associated with higher levels of participation (Osborne et al. 2008; Rotolo 1999; Sandstrom and Alper 2019).

3.2.3 The Current Study: Social Integration and PANs

Past literature has thus fully documented the demographic correlates of personal network structure and voluntary participation. However, relatively little work considers the overlap between the personal and associational aspects of an individual's ego network. While many researchers mention that network members share different social spaces (Alba and Kadushin 1976; Breiger 1974; Feld 1981; Mollenhorst 2009; Mollenhorst et al. 2012; Pescosolido and Rubin 2000; Popielarz and McPherson 1995; Simmel 1955), little research explores this overlap directly. While a limited number of studies have explored how voluntary association memberships influence personal network structure (van den Berg, Arentze, and Timmermans 2012; Davis et al. 2006; van Emmerik 2006; Mollenhorst et al. 2012), these studies fail to directly link an ego's personal ties to their associative ties.

This study takes up this problem by utilizing the measures of network structure developed in Chapter 2, which fully incorporate the associative and personal aspects of ego networks. In what follows, I (1) describe the structural and compositional features of personal affiliation networks and (2) identify whether social integration varies by individual characteristics. Below, I detail hypotheses related to both of these goals.

3.2.4 Hypotheses

3.2.4.1 Hypotheses 1–4: The Distribution of PAN Measures and the Relationship between Them

The first set of hypotheses describe the PAN measures and their relationship to each other. My goal is to understand the basic structure and composition of personal networks after incorporating associational and personal ties together. The hypotheses are based on known relationships between network properties, extended to the particular case of PANs. For example, while voluntary associations may diversify ties, having more ties to associations will result in a larger network and therefore may reduce its overall cohesion (e.g., density). Thus, I hypothesize that common network measures, such as degree and density, may be associated with co-membership PAN measures, density, and overall PAN cohesion.

> **Hypothesis 1:** Personal network degree will be positively associated with voluntary association degree—as those with larger personal networks can be expected to have more connections to other spaces in their social environment (i.e., voluntary associations).
>
> **Hypothesis 2:** Voluntary association degree and PAN degree will be negatively associated with personal network density and PAN cohesion measures—as the spread of a PAN increases, so does the number of possible ties; as a result, overall connectivity is expected to be lower compared to smaller networks.
>
> **Hypothesis 3:** Personal network density will be positively associated with co-membership density, PAN cohesion measures, and all co-membership specific measures—as having a tightly knit personal network increases the likelihood of sharing common ties across other spaces in the social environment.
>
> **Hypothesis 4:** Egos with any co-membership ties will be positively associated with personal network degree, voluntary association degree, and personal network density—as sharing multiple social contexts with individuals provides access to a broader set of social connections, which results in a larger and denser PAN compared to that of egos without any co-membership ties.

3.2.4.2 Hypotheses 5–9: Ego Demographic Correlates of PAN Measures

The second set of hypotheses are specific to the ego demographic correlates of PANs. For these hypotheses, I use past literature as a baseline: the derived hypothesis represents what would be expected if the newly derived PAN measures generate results similar to those of past research using simpler measures. Pulling from the literature on personal networks and voluntary association participation, I expect the following structural and compositional differences in PAN by gender, race, education, religion, and age:

Hypothesis 5: Women will have a higher proportion, magnitude, and concentration of co-membership ties compared to men (any co-membership, proportion co-member, proportion of co-members in voluntary associations, average co-membership, average co-members in voluntary associations, concentration of co-membership, and concentration of alters in voluntary associations).

Hypothesis 6: White egos, compared to non-white egos, will have larger PANs (personal network degree, voluntary association degree, and PAN degree), but their PANs will be less dense (personal network density, co-membership density, and PAN density).

Hypothesis 7: More highly educated egos are expected to have larger PANs (personal network degree, voluntary association degree, and PAN degree), but the PANs will be less dense and less cohesive (personal network density, co-membership density, PAN density, fraction in the largest component, and fraction in the largest bicomponent) than those of less-educated egos.

Hypothesis 8: All religiously affiliated egos will have larger, more dense, and more cohesive PANs than non-affiliated egos (personal network degree, voluntary association degree, PAN degree, personal network density, co-membership density, PAN density, fraction in the largest component, fraction in the largest bicomponent).

Hypothesis 9: Older egos will have a higher proportion, magnitude, and concentration of co-membership ties compared to younger egos (any co-membership, proportion co-member, proportion of co-members in voluntary associations, average co-membership, average co-members in voluntary associations, concentration of co-membership, and concentration of alters in voluntary associations).

3.3 DATA AND METHODS

3.3.1 Data: The 2006 National Voluntary Association Study (NVAS)

The 2006 National Voluntary Association Study (NVAS) is a re-interview sample of individuals who completed the 2004 General Social Survey (GSS) module on Voluntary Associations and Networks. The NVAS was collected to better understand the role of voluntary associations in individuals' lives. Its sampling frame was drawn from respondents of the 2004 GSS both with and without voluntary experience. Through telephone interviews, collected by NORC, the NVAS was completed by 860 individuals yielding a nearly 60% response rate. Many of the same survey instruments used in the 2004 GSS module were also included in the 2006 NVAS re-interview survey, including survey items related to the personal networks and the voluntary association memberships of respondents.

3.3.2 Personal, Associational, and Co-membership Features of the 2006 NVAS

Like the 2004 GSS, the NVAS gathers data on the core discussion partners of individuals as well as their associative habits (Marsden 1987; McPherson et al. 2006; Renzulli and Aldrich 2005). In the NVAS, questions about voluntary association memberships were asked first, followed by a "discuss important matters" name generator. The co-membership ties between each alter and individual (ego) were included in the name interpreter that was gathered in the network section of the survey.

Individuals were first asked about their membership in 16 types of voluntary associations using the following prompt: "*We would like to know something about the groups and organizations to which individuals belong. I will read a list of various kinds of organizations. Could you tell me whether or not you are a member of each type? Please respond 'yes' or 'no' to each one*." The organizational types included fraternal groups; service clubs; veterans' groups; political clubs; labor unions; sports groups; youth groups; school service groups; hobby or garden clubs; school fraternities or sororities; nationality groups; farm organizations; literary, art discussion, or study groups; professional or academic societies; church-affiliated groups;[6] and any other groups.

A section on social networks follows the groups section. Here, ego networks are measured as core discussion networks, specifically operationalized as those with whom you discuss important matters (Marsden 1987; McPherson et al. 2006). The name generator asked respondents to list up to five alters under the following condition: "*From time to time, most people discuss important matters with other people. Looking back over the last six months—who are the people with whom you discussed matters important to you? Just tell me their first names or initials*." In 2004, ego networks were similarly operationalized as core discussion partners; however, respondents were able to nominate up to six alters rather than five. The

[6] Denominations, religious communities (such as congregations, synagogues, and mosques), and other faith groups were all included as "church affiliated groups." Interviewers were provided the following instructions: "'Church affiliated groups can include denomination and/or congregations. Also, it should include religious groups such as synagogues, mosques, and other such faith groups as well as groups associated with the same."

respondent was then asked detailed questions about each alter (name interpreter), including questions about ties between alters (alter-alter ties).

An additional generator for co-membership was included in the networks section of the survey. By pairing the association memberships that had been elicited from respondents with alter nominations, the NVAS measured co-membership ties and alter-to-alter ties. A co-membership tie indicates that alter *i* is a member of association *j*. For each alter, the respondent was asked if alter *i* was co-member (yes/no). If alter *i* was identified as a co-member, the respondent was prompted to detail whether alter *i* was a member of each association membership the respondent had previously identified. Therefore, the data permits researchers to identify whether any given alter is a member of any given voluntary association listed by an individual. The NVAS's direct mapping of alter-association ties is an essential component for constructing PANs, as previous research has not been able to extend beyond a single role relation of "co-member" or has been limited to inferring shared contexts. Here, however, each alter-alter tie and each alter-association tie is captured.

The specific measures used to capture co-membership are detailed below. Through a series of questions, co-membership was elicited for each alter and organization pair. Specifically, for each alter, the respondent was asked about the role relation of the given alter (typical multiplex relation). Respondents were prompted as follows: "*I am going to read you a list of some of the ways in which people are connected to each other. Some people can be connected to you in more than one way. For example, a man could be your brother and he may belong to your church and be your lawyer. I will read a name, and then please tell me yes or no for each of the ways that this person may be connected to you*." The respondent was first asked if the alter was related kin (spouse, parent, sibling, child, other family, or not related), then asked about non-kin relations, including “co-worker”; “a member of a group, like the ones we mentioned before”; or “neighbor, friend, and advisor.”

Then, if an alter was also “a member of a group, like the ones we mentioned before,” up to four follow-up questions were asked. First, respondents were asked about the general co-membership relation: “*Do you and [ALTER X] both belong to one or more of the same groups?*” If that alter was indicated as a co-member, they were then asked which groups the alter was a member of. Here, the option of shared membership was conditioned on the voluntary associational memberships reported by egos in the previous section; respondents were not asked about co-membership for associations of which they themselves are not members. Additional data were also collected to provide more detail pertaining to the alter-association ties, including whether the relationship was formed in an organization (i.e., did ego meet alter *i* in a voluntary association) and, if so, in which organization (i.e., in which association (*j*) did ego meet alter *i*).

Overall, the NVAS contains information on the voluntary association memberships of egos, their personal network characteristics (information about alters and alter-alter ties), and the co-membership ties of each alter-association pair. Each of these elements can be used to construct a personal affiliation network (PAN) using sampled ego network data. Given that my main goal is to describe the structural patterns of overlap between personal and associational networks, I limit my sample to include only individuals that have potential for overlap. Definitionally, co-membership can only occur in PAN where there is at least one alter and one association. Without one or the other, there are no possible alter-association ties.[7] Therefore, for these analyses, the sample is limited to egos that have at least one nominated alter and one voluntary association membership (n = 636).[8]

3.3.3 Dependent Variables: PAN Measures[9]

To assess individual social integration that incorporates personal and association ties in ego networks, I rely on the PAN measures summarized in the previous chapter (Chapter 2). Here, I briefly describe each measure and its utility. Network measures such as size, density, and cohesion are widely used in social science research, especially for personal (ego) networks (Marsden 1993; Perry et al. 2018). Yet, few studies have explored how such measures can be used to capture more than personal ties alone. In fact, few studies even measure how named alters are tied to an ego's other social spaces. Assuming a unique data structure, such as that of the NVAS, I constructed 15 measures of social integration that directly capture personal and associational ties in a single network context; these measures are conceptualized in four broad categories: network size, network density, co-membership specific, and PAN cohesion.

Three network size measures capture the personal, associational, and total spread of an ego's PAN: personal network degree, voluntary association degree, and PAN degree. *Personal network degree* is a count of the number of named alters

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[7] For this demonstration, isolated individuals (those without personal and/or associational ties) are excluded. Future research should explore the ways that isolation manifests both within and between each of these contexts.
[8] Three individuals were excluded from the final analytic sample due to missingness on the weight variable. Only one of the three egos had shared memberships with the alters.
[9] All measures present here exclude ego from their calculation, including ties between an ego and nominated alters as well as between an ego and voluntary association memberships.

nominated by an ego. It is commonly used to measure the spread of an individual's immediate social environment and to predict individual-level outcomes.

Similarly, *voluntary association degree* is the total number of voluntary associations to which an ego belongs. More generally, the degree of voluntary association memberships captures social integration, tying individuals to groups rather than just to other individuals. This measure is used as an indicator of civil engagement and social capital of individuals.

PAN degree is the total number of named alters (i.e., personal ties) and voluntary association memberships (i.e., associational ties) of an ego. It captures the full extent of an individual's ties to individuals and to groups.[10] For a sample of egos with at least one discussion partner and one voluntary association membership, personal network degree ranges from 1 to 5, and voluntary association degree ranges from 1 to 12.[11] PAN degree is the summed total of personal network degree and voluntary association degree and ranges from 2 to 16.

Three measures capture the connectedness of alters and associations within PANs: personal network density, co-membership density, and PAN density. The measures focus on the ties between nodes rather than the number of nodes in the network. *Personal network density* indicates the connectedness of discussion partners, focusing only on alter-alter ties—that is, whether specific alters know each

[10] It is not possible to know the extent of close personal ties shared by individuals, as the ego network name generator was capped at five named alters. Further research should examine the extent to which nontruncated ego network members may also share other types of ties with egos.
[11] The summed voluntary association is limited to all memberships (15) minus the "other groups" category. Respondents (egos) were asked a follow up question about different types of other groups, but the other informal group memberships were not asked in the co-membership portion of the survey. Therefore, I limit voluntary association memberships to associations which had co-membership elicited.

other. It is the proportion of ties that exist between alters divided by the total number of possible alter-alter ties.

Co-membership density, in contrast, focuses on the shared memberships of an ego and their alter(s) (i.e., co-membership). It indicates the rate of overlap between the nominated alters and the voluntary associations ego is a member of. Because ties between the associations themselves are unknown, this density measure is calculated as the proportion of alter-association ties that exist divided by the total possible alter-association ties.

Finally, *PAN density* extends beyond a single type of tie to measure the connectedness of an individual's immediate social environment, capturing both alter-alter and alter-association ties. Substantively, it measures how integrated an individual is to persons and associations. Operationally, PAN density combines personal network and co-membership density; it is the proportion of actual alter-alter and alter-association ties divided by the total number of possible alter-alter and alter-association ties.

Each density measure ranges from 0 to 1, where "0" suggests no connectivity and "1" suggests complete connectivity between each pair of nodes. Importantly, each co-membership specific measure has the possibility of a structural zero when an ego has no co-membership ties—where no alters share common memberships with the voluntary associations of the ego (alter-association ties). Variation in co-membership density, therefore, only occurs when egos have co-membership ties within their PAN.

The next measures focus on the co-membership features of the PAN. These co-membership-specific measures are used to capture varying patterns of overlap between alters and voluntary associations. I developed three sets of measures of increasing complexity that focus on alter-association ties within PANs.

The first set of measures relate to the proportional composition of PAN and are similar to other proportional composition measures commonly used in ego network research (e.g., proportion kin). *Proportion co-member* identifies the total proportion of alters who share at least one voluntary association membership with an ego. Substantively, proportion co-member can be used to identify how salient co-memberships are for alters (i.e., it shows the overlap between personal and associational contexts). *Proportion of voluntary associations with co-members* measures the proportion of an ego's voluntary associations that have shared memberships with alters. Here, the focus is on the saliency of shared memberships within organizations. Each of the proportional composition measures ranges from 0 to 1.

One key drawback of the proportional composition measures is their inability to gauge the number of shared memberships a given alter may have with an ego. For instance, in order to understand if alters tend to have many co-memberships, a measure needs to account for the multiple shared ties an alter can have. *Average co-membership*, the average number of co-membership ties a given alter has, accomplishes this. Average tie counts can also be applied to voluntary associations—capturing the average number of co-members that share memberships within a given association. The *average number of co-members in voluntary associations* measure provides this information. Both average co-membership and average number of co-members in voluntary associations have a maximum value of 5.

While they are useful for understanding varying levels of co-membership, the above measures cannot differentiate between co-membership ties that are isolated to a single alter and co-membership ties that are evenly distributed among alters. To account for the variability of co-membership ties, two additional co-membership measures are used: concentration of co-membership and concentration of alters in voluntary associations. First, *concentration of co-membership* measures the variance of co-membership ties specific to alters. Substantively, concentration of co-membership captures the extent to which co-membership ties are concentrated across alters. Second, *concentration of alters in voluntary associations* measures the extent of variation in co-membership ties across voluntary associations. This measure can distinguish, for example, between a PAN in which one association (e.g., church) is full of co-members while all others have none and a PAN in which voluntary associations have more evenly distributed shared memberships.

Both concentration measures are continuous, where a value of 0 references no variability—either because there are no co-membership ties or because co-membership ties are evenly distributed across alters or associations. Higher values refer to higher variability in co-membership ties, where specific alters or associations have more highly concentrated co-membership ties. Concentration of co-membership has a maximum value of 8.9, whereas the concentration of alters in voluntary associations has a maximum value of 12.5.

While the PAN degree and PAN density measures are able to account for personal and voluntary association ties simultaneously, neither shows the robustness of an individual's PAN. To better account for a PAN's structural variability, I use two measure that capture the cohesiveness of the network. First, the *fraction in* *the largest component* is a minimal measure of cohesion, capturing the proportion of nodes that are connected by at least one path. As a measure of maximal cohesion, the *fraction in the largest bicomponent* identifies the proportion of nodes that are connected by at least two independent paths. Both are proportional measures (ranging from 0 to 1) that identify the fraction of alters in the most cohesive component of the network. Both PAN cohesion measures incorporate all node and tie types concurrently.

Table 3.1 Summary of Personal Affiliation Network (PAN) Measures

	Description	Bounds
1. Network Size Measures	*Extent of social ties*	
Personal Network Degree	Total number of discussion partners	1-5
Voluntary Association (VA) Degree	Total VA memberships of ego	1-12
PAN Degree	Total personal and VA ties of ego	2-16
2. Network Density Measures	*Network structure characteristic*	
Personal Network Density	Connectedness of personal ties	0-1
Co-membership Density	Rate of overlap between alters and associations	0-1
PAN Density	Connectedness of full social environment	0-1
3. Co-membership Specific Measures		
Proportional Composition	*Saliency of alter-association ties*	
Proportion Co-member	Saliency of co-members (alters)	0-1
Proportion of VA with Co-members	Saliency of co-membership within VA	0-1
Magnitude of Co-membership	*Level/Rate of alter-association ties*	
Average Co-membership	Average number of co-memberships per alter	0-5
Average Co-members in VA	Average number of co-members in VA	0-5
Co-membership Concentration	*Variability in alter-association ties*	
Concentration of Co-membership	Variability of co-membership within alters	0-8.9
Concentration of Alters in VA	Variability of alters in VA	0-12.5
4. PAN Cohesion Measures	*Contextual measure of cohesiveness of PAN*	
Fraction in the Largest Component	Minimal cohesion	0-1
Fraction in the Largest Bicomponent	Maximal cohesion	0-1

Table 3.1 contains the full set of 14 PAN measures broken into four sets: (1) network size measures, (2) network density measures, (3) co-membership-specific

measures, and (4) PAN cohesion measures. For each measure, a brief description and the bounds specific to the 2006 NVAS data are noted.

3.3.4 Independent Variables: Ego Characteristics

Many demographic variables have been used to understand the differences in structure, composition, and utility of personal networks. To explore ego characteristics associated with PAN structure, I include five ego demographic variables: sex, race, education, religion, and age. Sex is coded as a dichotomous variable (male = reference). Race is coded as a dichotomous variable (white/non-white).[12] Education is coded as a three-category variable: less than BA (reference), BA, and higher than BA.[13] Religion is coded as a four-category variable: Protestant (reference), Catholic, other, and none. Finally, age is a continuous variable measured in years.

3.3.5 Analytic Strategy

Two sets of analyses are used to (1) identify the structural and compositional distribution of personal affiliation networks (PANs) on sampled data and (2) identify whether any ego demographic correlates are associated with each PAN measure.

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[12] Race is coded in this way because only a small proportion of individuals identified as a race other than white.

[13] In additional analyses not presented here, other ways of categorizing education were created. For example, in one analysis, education was coded as a binary indicator (less than BA/BA+). In another analysis, additional categories were used: less than HS, HS or some college, BA, BA+). Given that the sample was overwhelmingly highly educated (approximately 54% were coded as BA+), the three-category variable was used in all analyses presented here.

3.3.5.1 Analyses Part I: The Distribution of PAN Measures and the Relationship between Them

I rely on univariate and bivariate statistics to test the PAN measures constructed in the previous chapter (see Table 3.1 for a summary of all measures). I first use univariate statistics to describe the distribution and pattern of PANs using the sampled data from the NVAS as a case study. Second, to test the first four hypotheses (Hypotheses 1–4), I examine the relationship between commonly used network measures (personal network degree and personal network density) and the PAN-specific measures I developed. The goal here is to identify the linear relationship between the new measures and commonly used measures. When evaluating the relationship between each pair of variables, I assume that there are rough cut points: I interpret a correlation coefficient greater than 0.70 as a strong linear relationship, 0.31 to 0.69 as a moderate linear relationship, and less than 0.30 as a weak linear relationship. Any correlation of "0" would indicate no linear relationship.

All univariate and bivariate analyses are described in a stepwise fashion, working from simplest to most complex, ordered as follows: (1) network degree measures, (2) network density measures, (3) co-membership-specific measures, and (4) PAN cohesion measures.

3.3.5.2 Analyses Part II: Ego Demographic Correlates of PAN Measures

After detailing how the PAN measures are distributed using the 2006 NVAS, I transition to a second set of analyses, exploring the association between ego demographic characteristics and PAN structure and composition. Using univariate, bivariate, and multivariate methods, I explore how the various graph-based summary measures differ across characteristics. First, using univariate statistics, I describe the sample of egos in the 2006 NVAS along five common demographic dimensions—sex, race, education, religion, and age. For additional detail about the relational and membership characteristics of PANs, I describe the types of relationships, the average relationship length and interaction frequency with alters, and the type of voluntary association to which egos belong.

Then, focusing on hypotheses 5–9, I first explore the bivariate association between each ego characteristic and each PAN measure. The bivariate analyses, which rely on t-test and pairwise mean comparisons, identify any significant associations between a single demographic characteristic of an ego and the corresponding network measure. Finally, I run two regression models for each PAN measure. The first model employs weighted OLS regression to predict the PAN measure of interest as a function of all five ego demographic covariates.[14] The model is formally shown in Formula 3.1, where y_i represents the given PAN measure of interest.

$$y_i = \beta_0 + \beta_1 sex_i + \beta_2\, race_i + \beta_3 education_i + \beta_4 religion_i + \beta_5 age_i + e_i \qquad (3.1)$$

The second model, which also includes all covariates from the first model, adds any co-membership as another covariate in the model. Given that many of the PAN measures are structurally different depending on whether co-memberships

[14] Sensitivity analyses were run using specified models to account for the truncated (degree measures) and bounded (proportion 0-1) (density, proportional composition, and cohesion measures) nature of the dependent variables. For the truncated degree measures, I ran truncated Poisson regressions (`tpoisson`), and for the proportional measures, I performed fractional regressions (`fracreg`). All specialized models yielded consistent findings, and, therefore, for ease of interpretation I present all models using the OLS regression results.

(alter-association ties) are present or absent, I control for as much of the structural variation as possible. The second model is formally shown in Equation 3.2.

$$y_i = \beta_0 + \beta_1 sex_i + \beta_2\, race_i + \beta_3 education_i + \beta_4 religion_i + \beta_5 age_i + \beta_6 any\ co - membership_i + e_i \tag{3.2}$$

All multivariate models are presented in a single summary table for ease of interpretation, given the number of dependent variables. The PAN measures are listed in order: degree measures, density measures, co-membership-specific measures, and cohesion measures. In each regression model, higher predicted values of a given measure indicate greater integration of an ego. For example, the higher the value of PAN degree, the more alters and voluntary associations the ego is tied to.

All univariate, bivariate, and multivariate analyses were conducted in Stata version 16. I accounted for the complex nature of the survey data by using weights and strata. I used the svy estimation commands in Stata, specifically relying on the svy: regression command and Taylor Series Linearization methods for variance estimation.

3.4 RESULTS

3.4.1 Results Part I: The Distribution of PAN Measures and the Relationship between Them

3.4.1.1 Univariate Results: Network Size Measures

The degree distribution of personal, co-membership, and personal affiliation networks (PAN) in the NVAS are displayed in Figure 3.1, where egos tend to have more core discussion partners compared to voluntary association memberships. Specifically, individuals tend to report a high number of discussion partners, with 70% of the sample reporting three or more people with whom they discuss important matters. The average personal network size is 3.41 (see Table 3.2). This personal network degree average is high, especially compared to the 2004 GSS, which had an average discussion partner network size of 2.67 (calculated from McPherson et al. 2006; 1-5+ average). The higher-than-expected average of core discussion partners in the 2006 NVAS may be explained by the sample selection of this study. Because the main goal of this analysis was to capture patterns of overlap between personal and associational components of an individual's social environment, the sample was limited to those with at least one associational membership and one core discussion partner.[15] Therefore, this selection criteria may be capturing more socially integrated individuals and driving up this average.

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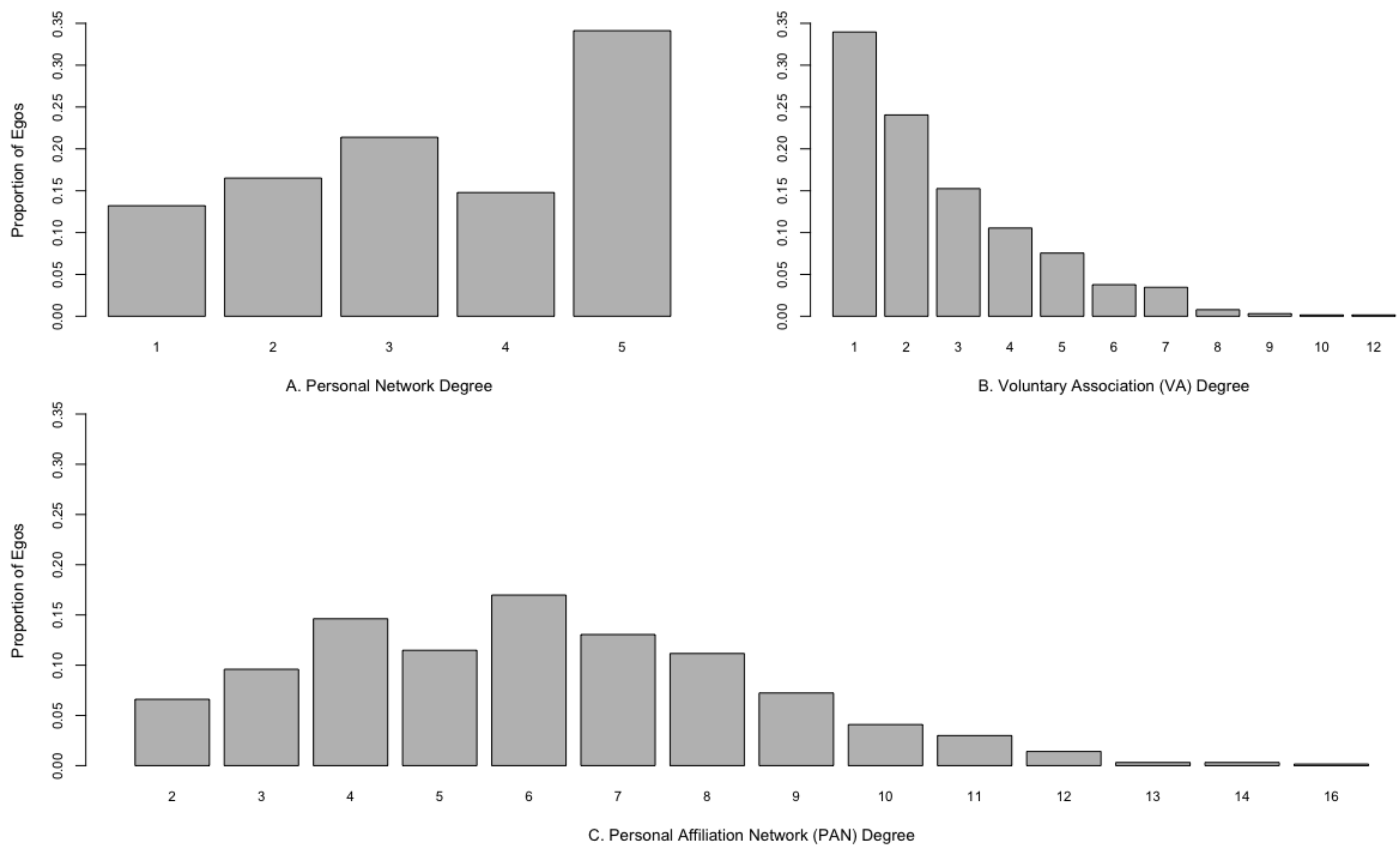
[15] Even when including socially isolated egos, however, the average personal network size remains higher than that identified by McPherson et al. (2006): 3.04; n = 853.

Figure 3.1 Degree Distribution of Network Size Measures: Personal Network Degree, Voluntary Association Degree, PAN Degree (n = 636)



Voluntary association degree is less uniformly distributed than personal network degree. On average, egos are members of 2.67 voluntary associations (see Table 3.2). As seen in the second plot of Figure 3.1 (B), voluntary association degree is right skewed. This skewed distribution indicates that few egos have large numbers of voluntary association memberships: more than two-thirds of egos are members of two or fewer voluntary associations. This may highlight differences between associational and interpersonal ties: voluntary associations require a different level of commitment and maintenance than personal network ties. It may be easier to maintain many personal ties than to maintain many associational ties.

When looking at the full degree of PAN, egos have an average combined social environment of 6.06 discussion partners and voluntary association memberships. While PAN degree is more uniformly distributed than voluntary association memberships, it captures the spread of individuals' associative and personal networks (see Figure 3.1). The ratio of alters to associations is 3.41:2.67, suggesting that for every voluntary association membership, egos have an average of 1.27 core discussion partners.

3.4.1.2 Univariate Results: Network Density Measures

The network density measures capture different dimensions of network structure. In addition to the typically measured personal network density, I explore the density distribution of co-membership—linking alters and associations—and the density distribution of the full PAN (alter-alter and alter-association ties). Table 3.2 details the average density across all egos as well as the distribution of each density measure.

The personal network density measure indicates that core discussion networks are densely connected, with mean density of 0.699. This overall density is slightly higher than the average reported by McPherson et al. (2006) of 0.66. There is a slightly higher proportion of networks with a density of 1, with nearly 50% (0.498) of the sample having fully connected personal networks, where all possible ties exist between alters. No ties between alters (density = 0) are reported by 16% of the egos. Among egos with a personal density of zero, 84% (n = 86) have one reported discussion partner, and the other 14% (17) are completely disconnected (i.e., have no alter-alter ties).

Table 3.2 Weighted Descriptive Statistics of Network Size and Network Density Measures

		Mean/P	SD	Range
Network Size Measures				
Personal Network Degree		3.411	1.440	1-5
Voluntary Association Degree		2.672	1.818	2-12
PAN Degree		6.083	2.489	2-16
Network Density Measures				
Personal Network Density		.699	.375	0-1
	0	.162		
	> 0-.33	.062		
	.34-.5	.071		
	.51-.9	.207		
	1	.498		
Co-membership Density		.206	.265	0-1
	0	.377		
	> 0-.33	.430		
	.34-.5	.097		
	.51-.9	.040		
	1	.055		
PAN Density		.398	.254	0-1
	0	.113		
	> 0-.33	.355		
	.34-.5	.257		
	.51-.9	.220		
	1	.055		
	N	636		

Shared memberships (alter-association ties), however, tend to be less tightly knit than personal networks. Recall that co-membership density measures the relative overlap between alters and associations. Here, a co-membership density of 0.33, for example, would indicate that one-third of the possible co-membership ties exist. In the NVAS sample, the average co-membership density in PAN is 0.206 (see Table 3.2). This indicates that, on average, one-fifth of the possible co-membership ties exist within PANs. No overlap between personal and associational ties is reported by 38% of the sample, and only 5% have full overlap, where personal and associational networks are fully integrated with each other. Among egos with some connections between alters and associations, 44% are loosely knit, with having one-third or fewer ties.

The differences between the density distribution of personal networks and co-membership ties aligns with previous research suggesting that personal ties are more tightly knit than ties to the broader community. Some prior studies have highlighted the dense nature of personal networks—specifically core discussion networks (Marsden 1987, 1993; McPherson et al. 2006)—while other research has explored the diversity and structure of shared social contexts (Davis et al. 2006; Mollenhorst 2008; Pescosolido and Rubin 2000). Both personal and associational ties vary in strength, duration, utility, and maintenance. We would not expect co-membership networks to be as tightly woven as personal networks, as they are tied to "weaker" ties that are definitionally more diffuse.

An important takeaway, however, is that co-membership density measure suggests overlap between personal and associational ties, even if the overlap is diffuse. Having shared memberships with alters may lead to additional access to resources, support, and connections that personal networks alone may not offer. When we consider overall PAN density, we can measure the collective connectivity of personal and associational ties. In Table 3.2, we see that PAN density, or the total connectivity of the personal and associational network of an ego, tends to be relatively dense with 39% of ties present.

The overall spread and connectedness of PAN described above highlights the important contribution of this research. Before now, little research has been able to measure the overlap between personal networks and association participation directly. While some studies illuminate the number of contexts people share (Mollenhorst et al. 2012) and emphasize the importance of social connectivity beyond personal ties (Cornwell 2012; Cornwell and Waite 2009), the actual extent of overlap remains unknown. Using a PAN data structure, I am able to highlight the strikingly high level of shared contexts that exist among egos: more than 60% of respondents have some overlap between their personal and associational networks. Nearly two-thirds of respondents that have the potential for overlap between their personal and associational spaces share common ties. When we include isolated individuals in the total, more than 46% of egos (395/853) still have overlapping personal and associational ties. This finding suggests that those core to our personal environment are linked to other spaces in our social environment as well.

While the network degree and network density measures can provide information on the extent of personal and associational ties and the level of connectivity between the two, they can neither provide information about how co-membership ties are patterned nor capture the relative structure of PAN. Therefore, to better measure the full structural composition of PAN, I rely on co-membership-specific measures to identify the extent of co-membership ties (alter-association ties) within PAN, their magnitude, and their concentration.

Table 3.3 Weighted Descriptive Statistics of Co-membership-Specific Measures

	Mean/P	SD	Range
Proportional Composition			
Proportion Co-member	.380	.376	0-1
0	.377		
>0-.49	.232		
.5	.075		
>.5-.9	.140		
1	.176		
Proportion of VA with Co-members	.383	.375	0-1
0	.377		
>0-.49	.186		
.5	.154		
>.5-.9	.103		
1	.180		
Magnitude of Co-membership			
Average Co-membership	.516	.703	0-5
Average Co-members in VA	.692	.898	0-5
Concentration of Co-membership			
Concentration of Co-membership	.293	.697	0-8.9
Concentration of Alters in VA	.750	1.683	0-12.5
N	636		

3.4.1.3 Univariate Results: Co-membership Specific Measures

Table 3.3 presents the univariate statistics for each co-membership-specific measure. The proportional composition of PAN shows that, on average, 38% of alters are co-members. If we look at the distribution of the proportion co-member, however, we can see that almost 40% (0.391) of alters have half or more of their alters as co-members. The overall distribution of the proportion of voluntary associations with co-members is similar to that of proportion co-member, where, on average, 38% of an ego's voluntary associations have at least one alter who shares a membership with the same association(s). The proportion of voluntary associations with co-members, where at least have of the associations have shared members is slightly higher: 44%

of ego's voluntary associations have at least one core discussion partner who is also a co-member.

While both the proportion co-member and proportion of voluntary associations with co-members measures share similar distributions, they capture distinct features of co-membership ties. In Table 3.4, we can see that when you compare the proportion co-member measure to the proportion of voluntary associations with co-members, only about 20% have the same values for both (not including the roughly 38% of egos with no co-membership ties). Of the 62% of egos that have overlap in their personal and associational networks, roughly 41% differ in the proportion of co-members and the proportion of voluntary associations with co-members.

Table 3.4 Crosstab of Proportion of Co-member by Proportion of VA with Co-members

		Proportion of VA with Co-members					
		0	>0-.49	.5	.51-.9	1	Total
Proportion Co-member	0	.377	—	—	—	—	.377
	>0-.49	—	.090	.059	.029	.054	.232
	.5	—	.020	.022	.006	.028	.075
	.51-.9	—	.043	.036	.030	.031	.140
	1	—	.033	.038	.038	.067	.176
	Total	.377	.186	.155	.103	.180	1.00

Shading indicates the same proportional composition for both measures.

The differences between the proportional composition measures highlight how shared memberships operate differently for alters and for voluntary associations. Egos, for example, tend to have more alters than voluntary association memberships, yet we see that roughly 18% of egos share at least one common membership with every alter (-.176). At the same time, there are variations across associations sharing co-members. This suggests that different associations may be more (or less) communal (or tied to an ego's close personal ties). Take, for instance, the distinction between a church and a sports club. While an ego may attend church with many core network members (e.g., spouse, parents, friends), their sport club participation may be serving an alternative purpose. Put differently, some organizations may serve integrating purposes that are communal (or at least take place within a communal context), while others may serve as a separate, individualized hub of connectivity.

More nuanced variation in the magnitude and concentration of co-membership is captured in the additional co-membership measures. However, the average number of co-membership ties for both alters (average co-membership) and voluntary associations (average co-members in voluntary associations) is low: 0.516 and 0.692, respectively (see Table 3.3). Additionally, although there is a wide variation in the concentration of co-membership ties (0–8.9 and 0–12.5), co-membership ties are not very concentrated: 0.293 and 0.750, respectively (see Table 3.3).

3.4.1.4 Univariate Results: PAN Cohesion Measures

Overall, PANs tend to be highly cohesive, both using the minimal (component) and maximal (bicomponent) cohesion measures. Table 3.5 presents the univariate statistics for both cohesion measures. The average proportion of nodes (both alters and associations) in the largest component is just shy of 70% (0.697). Roughly 70% of nodes are connected by a single path. The proportion of those maximally connected are lower (0.549), on average, but this is unsurprising. Maximal connectivity requires nodes to be connected by at least two independent paths. Even so, there still more than 55% (0.549) of nodes are in the largest bicomponent. This suggests that there is a relatively high level of cohesion in PANs across all egos in the 2006 NVAS sample.

In sum, when employing the PAN measures constructed in Chapter 2 to the 2006 NVAS data, I identified three major characteristics: (1) There is a surprisingly high level of overlap between the personal networks and voluntary association networks of egos: 62% of egos have at least one alter who has a shared membership in one of their voluntary associations. (2) PANs are relatively dense and have relatively high cohesion. (3) Distinct variation exists within patterns of co-membership: alters vary in co-membership ties, and shared members vary across voluntary associations.

Table 3.5 Weighted Descriptive Statistics of PAN Cohesion Measures

	Mean/P	SD	Range
Fraction in the Largest Component	.697	.218	.125-1
Fraction in the Largest Bicomponent	.549	.268	0-1
N	636		

3.4.1.5 Bivariate Results: Correlation between Simple Network Measures and PAN Measures

To assess the first three hypotheses pertaining to the relationship between PAN measures, I examine the linear relationship between commonly used measures—personal network degree, personal network density, and voluntary association degree—and the PAN measures described above. Table 3.6 presents the correlations between each PAN measure and the three more commonly used measures (see Appendix 3.A for the full correlation matrix).

Specifically focusing on Hypothesis 1, I find support for a positive association between personal network degree and voluntary association degree. Although the association between personal network degree and voluntary association degree is relatively weak (0.176), a significant linear relationship is evident. As personal network size increases, voluntary association degree similarly increases.

Table 3.6 Correlation between Simple Network Measures and PAN Measures

	Personal Network Degree	Personal Network Density	Voluntary Association Degree
Network Size Measures			
Personal Network Degree	1.000	.408*	.176*
Voluntary Association Degree	.176*	.088*	1.000
PAN Degree	.699*	.297*	.827*
Network Density Measures			
Personal Network Density	.408*	1.000	.088*
Co-membership Density	-.036	.062	-.086*
PAN Density	.273*	.484*	-.257*
Co-membership Specific			
Proportional Composition			
Proportion Co-member	.084*	.117*	.297*
Proportion of VA with Co-members	.204*	.159*	-.034
Magnitude of Co-membership			
Average Co-membership	.041	.090*	.427*
Average Co-members in VA	.295*	.206*	-.040
Co-membership Concentration			
Concentration of Co-membership	.179*	.099*	.406*
Concentration of Alters in VA	.290*	.145*	.102*
PAN Cohesion			
Fraction in the Largest Component	.392*	.451*	-.314*
Fraction in the Largest Bicomponent	.442*	.635*	-.231*
N	636		

* Significant at $p < .05$

The second hypothesis concerning network size, density, and cohesion is partially supported. First, voluntary association degree is negatively associated with co-membership density (-0.086), PAN density (-0.257), and both minimal (-0.314) and maximal (-0.231) PAN cohesion measures. In the case of voluntary association degree, we would expect the overall connectivity and cohesiveness of PANs to decrease as membership increases. Less clear, however, is the relationship between overall PAN degree, density, and cohesion measures—in part because personal ties constitute a portion of the PAN degree measure itself. While voluntary association degree is clearly negatively correlated with density and cohesion measures, the relationship with PAN degree is more nuanced. In contrast to voluntary association degree, PAN degree is positively correlated with both personal network degree and personal network density: 0.699 and 0.297, respectively.

Finally, when exploring the relationship between tightly knit personal networks and co-membership-specific measures, I find support for Hypothesis 3, as personal network density is positively correlated with every co-membership-specific measure. Although the relationship is weak for most of the co-membership measures, a linear increase in network density correlates with an increase in the corresponding co-membership (alter-association ties) connectivity.

Overall, the significant bivariate relationship between simpler, commonly used network measures and the PAN measures (containing detailed tie types) highlights the complexities of social integration. Generally, having more social ties suggests higher levels of social connectivity; at the same time, however, having more ties increases the difficulty of activating all of the ties. Especially important for researchers is the relationship between personal network density and other PAN measures, including the PAN cohesion measures and all co-membership-specific measures: Those with higher levels of connectivity in their personal ties are also expected to have higher levels of integration on other measures, even those that are not partially composed of alter-alter ties. This further emphasizes the association between close personal ties and other social spaces, such as voluntary associations.

3.4.2 Results Part II: Ego Demographic Correlates of PAN Measures

Having discussed the structural and compositional features of personal affiliation networks (PANs) in the above analyses, I now transition to the second set of analyses focusing on the other aim of this chapter: to determine whether social integration varies by individual characteristics. I first describe the demographic characteristics of the sample, including a brief description of the types of alters and voluntary associations which constitute PANs in the NVAS. Then, to test Hypotheses 5 through 9, I use bivariate statistics to describe the relationship between each ego-level characteristic and each PAN measure, then employ multivariate statistics to predict each PAN measure as a function of all ego demographic correlates. The first multivariate model includes all ego-level characteristic as covariates, and the second model builds on the first, adding an additional indicator for co-membership ties (i.e., any co-membership).

3.4.2.1 2006 NVAS Sample Description

Table 3.7 displays the weighted descriptive statistics of ego characteristics for the sample of NVAS, limited to individuals with the potential for shared memberships. Of that sample, 59% identify as female, 21% are non-white, and the average age is 44.218 years. The sample is highly educated with roughly 27% having a bachelor's degree, 17% having a degree higher than a bachelor's, and the remaining 56% having less than a college degree. The majority of individuals are religiously affiliated: 52% identify as Protestant, 22% as Catholic, and 12% as other. The remaining 14% are not religiously affiliated.

Table 3.7 Descriptive Statistics of Ego Demographic Characteristics

		Mean/P
Sex (Female)		.592
Race (non-white)		.208
Education		
	< BA	.568
	BA	.267
	> BA	.165
Religion		
	Protestant	.522
	Catholic	.218
	Other	.121
	None	.139
Age (SD)		44.218 (16.071)
	N	636

Table 3.8 presents the relational characteristics and features of personal networks as a way to describe who makes up the core discussion networks of individuals and the landscape of their voluntary association memberships. The relational characteristics are specific to the types of alters within a PAN, where an ego could identify multiple roles associated with any given alter. Most notably, just under half (48%) of an ego's alters are kin, and roughly 55% are female.

The most commonly identified roles among alters are friend (98%), co-member of a group (74%), advisor (68%), spouse (47%), and co-worker (35%). More than half (60%) of egos have at least one non-spouse kin relation, 81% have at least one non-kin confidant, and 76% have at least one kin confidant. On average, core discussion partners are long lasting and frequently sought out: 75% of relationships have lasted five years or more. Additionally, the majority of egos (61%) have contact with alters at least weekly, with 23% of ego talking to alters almost daily.

Table 3.8 Structural Characteristics of Role Relations in Personal Affiliation Networks (PAN)

		%/mean (SD)
Relational Characteristics [a]		
Relation Type		
	Spouse	47.03
	Parent	25.99
	Sibling	19.66
	Child	15.74
	Other Kin	19.35
	Co-worker	34.95
	Co-member of group	73.60
	Neighbor	27.14
	Advisor	67.81
	Friend	98.26
	Other	31.78
Spouse is Only Confidant		5.83
At Least One Non-spouse Kin		60.31
At Least One Non-kin Confidant		80.52
At Least One Kin Confidant		76.22
Proportion Kin		48.02 (.357)
Network Composition		
Proportion Female		54.92 (.327)
Average Length of Tie		
	< 5 years	24.69
	5-10 years	39.24
	10 +	36.07
Average Contact Frequency		
	once a month or less	15.78
	~ once per week	61.37
	~ daily	22.85
	N	636

Note: The relation-specific measures are interpreted as the percentage of egos who nominated a spouse/parent/sibling/etc. as someone core to their network.
[a] An ego could identify multiple types of relations for a given alter (i.e., a spouse could also be a friend), and, therefore, the percentages do not sum to 100.

Table 3.9 presents information on the types of voluntary associations that egos are members of. Individuals are most likely to be members of church-affiliated groups (52%); however, only 12% of egos have church as their only membership. An additional 40% of church members have at least one non-church membership. Other highly frequented voluntary associations are professional or academic societies (22%), sports clubs (22%), and school service groups (20%).

Table 3.9 Voluntary Association Memberships of Respondents by Co-membership

	%
Voluntary Association Types [a]	
Fraternal groups	7.84
Service clubs	15.83
Veterans' groups	6.20
Political clubs	8.62
Labor unions	12.01
Sports clubs	21.58
Youth groups	13.97
School service groups	20.24
Hobby or garden clubs	12.22
School fraternities or sororities	5.65
Nationality groups	4.74
Farm organizations	3.73
Literary, art, study groups	13.06
Professional or academic societies	21.95
Church affiliated groups	51.81
Other groups	9.86
Church is Only Membership	11.79
Church Members with At Least One Non-Church Membership	40.02
N	636

Note: Each percentage displays the percent of egos that are members of specific group type (i.e., fraternal, service, veterans', etc.)
[a] Each ego may be a member of multiple types of voluntary associations; therefore, percentages do not sum to 100.

3.4.2.2 Bivariate Results: Ego Demographic Correlates of PAN Measures

Bivariate relationships between each PAN measure and ego-level characteristic are presented in Table 3.10 (the continuous variable "age" is not presented) and used to test Hypotheses 5 through 8. For these results, I only present significant mean differences between PAN and ego demographic characteristics, but full bivariate tables for each ego demographic covariate can be found in Appendices 3.B-3.E. All values in Table 3.10 represent the average network measure for each group. I employ group mean t-tests for mean comparisons between the sex and race characteristics, and I employ pairwise mean comparisons to test for mean differences across all education and religion categories. For the pairwise comparisons (variables with more than two categories), a pairwise mean comparison for each combination of significantly different PAN measures is presented in Table 3.11 (see Appendix 3.E and 3.F for the pairwise comparisons for all PAN measures).

Table 3.10 Table of Significant Bivariate Mean Differences between PAN Measures and Ego Demographic Characteristics

Sex[1]	**Male**	**Female**		
Personal Network Density	.655	.731*		
N	265	639		
Race[1]	**White**	**Non-white**		
Personal Network Degree	3.529	2.959**		
Personal Network Density	.735	.560***		
PAN Density	.413	.341*		
Fraction in the Largest Component	.711	.643**		
Fraction in the Largest Bicomponent	.570	.469**		
N	502	132		
Education[2]	**< BA**	**BA**	**> BA**	
VA Degree	2.369	2.983	3.210	
PAN Degree	5.688	6.430	6.876	
Personal Network Density	.656	.754	.756	
N	360	169	105	
Religion[2]	**Protestant**	**Catholic**	**Other**	**None**
Personal Network Degree	3.523	3.302	2.960	3.551
VA Degree	2.693	2.826	2.844	2.200
Co-membership Density	.232	.162	.228	.162
Proportion Co-member	.429	.338	.360	.274
Average Co-membership	.560	.421	.728	.312
Average Co-members in VA	.795	.552	.534	.657
Concentration of Alters in VA	1.008	.496	.357	.515
Fraction in the Largest Bicomponent	.578	.520	.487	.537
N	331	138	77	88

[1] Group means t-tests are performed to test for significant differences between groups.
[2] Pairwise mean comparisons are used.
p* < .05, ** *p* < .01, * *p* < .001

Consistent with previous research, women have denser personal networks than men. However, this differences between men and women does not hold for more detailed social integration measures. Rather, few sex differences exist for any of the proportion, magnitude, and concentration co-membership measures. While females have a higher average personal network density compared to males (0.731), they are not significantly different across any other PAN measure, including measures specific to shared memberships. This suggests that there is no initial support for Hypothesis 5: women will have a higher proportion, magnitude, and concentration of co-membership ties compared to men.

There are, however, clear structural differences by ego race specifically related to the connectivity of PANs. Consistent with previous research, egos who identify as white have larger denser, and more cohesive personal networks, on average, than non-white identifying egos. Interestingly, however, the number of voluntary association memberships and full PAN degree are not significantly different (see Appendix 3.C). These findings suggest initial support for Hypothesis 6: white egos, compared to non-white egos, will have larger but less dense PANs. These findings also allude to the complexity of social ties, where personal and associational ties may supplement personal ties for particular groups.

While the racial differences in network structure are maintained for some PAN measures, I find no educational differences in the either the combined personal and associational PAN measures (PAN density and PAN cohesion) or the co-membership specific PAN measures, which is contrary to previous studies (Horowitz 2015; McPherson et al. 2006; Roberts et al. 2008) and to Hypothesis 7. Egos with a BA (2.983; 6.430) and higher than a BA (3.210; 6.876), however, have more voluntary association memberships and larger PANs on average compared to those with less than a BA (2.369; 5.688). And consistent with previous research, personal network density is significantly higher among more highly educated egos (BA = 0.754, > BA = 0.756). So, although more highly educated egos do have more widely spread networks when incorporating both personal and associational ties, their overlap is no different than that for egos with less education.

Religious affiliation is the only ego-level characteristic associated with differences in the co-membership characteristics of PAN, although the patterns are not uniform. In the last block of Table 3.11, over half of the PAN measures vary significantly based on religion. Although the overall PAN degree does not vary across the religious affiliation of egos, personal network degree and voluntary association degree do.

Religiously affiliated egos (regardless of affiliation) have more voluntary association memberships on average (Protestant = 2.693; Catholic = 2.826; Other = 2.844)[16] than egos with no religious affiliation (2.200). Personal network degree, however, is significantly smaller for egos affiliated with “other” religions (2.960) than for Protestant and nonaffiliated egos (3.523; 3.551); Catholic egos’ personal network degree is not significantly different from that of any other religious affiliation (3.302).

[16] The means do not differ significantly when comparing religious affiliations.

Table 3.11 Significant Pairwise Group Mean Differences between PAN Measures and Education and Religion

Education	**<BA-BA**	**<BA->BA**	**BA->BA**
VA Degree	-.614*	-.841*	-.227
PAN Degree	-.742*	-1.188*	-.446
Personal Network Density	-.098*	-.100*	-.002

Religion	**Protest.-Cath.**	**Protest.-Other**	**Protest.-None**	**Cath.-Other**	**Cath.-None**	**Other-None**
Personal Network Degree	.221	.563*	-.028*	.342	-.249	-.591
VA Degree	-.133	-.151	.493*	-.018	.626*	.644*
Co-membership Density	.070*	.004	.070	-.066	.000	.066
Prop. Co-member	.091*	.069	.155*	-.022	.064	.086
Average Co-membership	.139*	-.168	.248*	-.307	.109	.416
Average Co-members in VA	.243*	.261*	.138	.018	-.105	-.123
Concentration of Alters in VA	.512*	.651*	.493*	.139	-.019	-.158
Fraction in the Largest Bicomponent	.058	.091*	.041	.033	-.017	-.050

* Significantly different means at $p < .05$

Additionally, the average concentration of alters in voluntary associations is significantly higher among Protestants compared to any other religious group. This suggests that Protestant egos tend to have denser and more highly connected co-memberships with alters and that these shared ties tend to be more concentrated in associations compared to other groups. One likely explanation is that Protestant egos have shared ties concentrated in their church membership. Alternatively, the personal relationships of Protestant egos could be driving these differences, where core network member ties are centered in the same types of associations. To determine which explanation is more likely, future research ought to explore the close personal network ties and voluntary association ties across religiously affiliated groups.

More generally, these findings partially confirm Hypothesis 8: all religiously affiliated egos will have larger, denser, and more cohesive PANs than nonaffiliated egos. It is important to note, however, that these differences are not ubiquitous across religious affiliation and may differ based on specific denominations; certainly, the differentiation is not as simple as secular versus nonsecular, a comparison often used in prior studies.

3.4.2.3 Multivariate Results: Ego Demographic Correlates of PAN Measures

Results from the weighted OLS regression models predicting each PAN measure are given in Table 3.12, where only significant coefficients are presented. The model for each PAN measure is presented in its own row, where the covariates included in the model are in the columns. For each of the 14 PAN measures, there are two models (a & b). Each PAN-dependent measure is numbered (1–14), and the rows corresponding to each model are labeled to match the measure. Full regression models can be found in the appendixes: see Appendix 3.H for the Network Degree Models, Appendix 3.I for the Network Density Models, Appendix 3.J for the Co-membership Specific Models, and Appendix 3.K for the PAN Cohesion Models.

Overwhelmingly, in the multivariate context, there are consistent findings when testing Hypotheses 5 through 8. As shown in Table 3.12, for example, I find no support for Hypothesis 5: women will have a higher proportion, magnitude, and concentration of co-membership ties compared to men. In fact, when controlling for any co-membership, women have an expected 0.045 lower comembership density and 0.049 lower proportion of co-members compared to men (see Table 3.10 row 5, M5b, and row 7, M7b). Furthermore, there are no significant gender differences for any of the co-membership-specific models (see Table 3.10; rows 8–12).

I find support for gendered differences in personal network density (not accounting for any alter-association ties): women have a 0.094 expected increase in personal network density compared to men. Even when controlling for any co-membership in PANs, gender remains a significant predictor of personal network density (0.092). However, similar differences do not exist for co-membership-specific measures or PAN cohesion measures. These nonsignificant gendered differences, although contrary to previous studies, illuminate something quite unique about PANs: the shared personal ties that women and men have may vary, but when accounting for additional tie types, such as associational ties, the same differences do not exist. Given the relatively high proportion of alters who share kin and spousal relations across personal networks, however, tight kin coupling may be reducing clear differences across co-membership ties. Put differently, men and women may both have high rates of shared co-memberships with their alters.

When exploring racialized differences in PAN, net of other ego-level characteristics, there are similarly unexpected findings. Although there are consistent racial differences in the size and density of personal networks, I find no significant differences in co-membership measures, contrary to the expected findings of Hypothesis 6. Although there are racial differences in personal network characteristics, there are not similar racialized patterns in social integration once accounting for alter-association ties. This suggests that the associative habits of nonwhite folks may be supplemental to personal ties, however, future studies should explore which, and to what extent, associational ties supplement personal ties. Moreover, the associative habits of individuals do not differ by race; indeed, even their shared memberships with alters do not differ. So, while both white and nonwhite racial groups share co-memberships at similar rates, their personal network characteristics shape their PAN more broadly.

White and nonwhite egos do not differ in the size of their PAN (see Table 3.10 row 3, column 2), but counter to Hypothesis 6, the overall cohesiveness of PANs for nonwhite egos is significantly lower than that of white egos. For both the minimal and maximal cohesion PAN measures (13 and 14), I find that even when controlling for any co-membership ties, nonwhite egos have a 0.051 and 0.084 lower expected fraction in the largest cohesive block of their PAN compared to white egos (see M13b and M14b).

Additionally, nonwhite egos have a 0.554 higher expected number of voluntary memberships than nonwhite egos (row 2, M2b), generally lower personal network degree (row 1, M1 a & b), generally lower personal network density (row 4, M4 a & b), and significantly lower PAN cohesion (rows 13 and 14; M13 and M14) than comparable white egos. The nonsignificant differences between racial groups when predicting the co-membership-specific measures (measures 8–12) confirm that the racialized differences in PAN cohesion is driven by the structural characteristics of personal networks between groups rather than the associative or co-membership features constituting their PAN.

The role of personal network structure, identified in these differences, contributes to an understanding of individual social integration, especially when incorporating personal and associational attributes within ego networks. These findings suggest that the associative involvement of egos and their shared memberships with alters are similar across racial groups. The broader communal ties do not define social integration for racial groups; rather, personal network differences differentially shape their social integration, where white egos have more minimally and maximally cohesive PANs, on average, compared to nonwhite egos.

When looking at educational differences across PANs, we can see consistencies with the bivariate results. Compared to egos with less than a bachelor's degree, more highly educated egos (bachelor's or higher than a bachelor's) have a higher rate of participation in voluntary associations, have an expected larger PAN, and have more densely connected personal networks (see Table 3.12 rows 2, 3, and 4). When controlling for any co-membership ties, egos with higher than a bachelor's degree have lower predicted co-membership density (-0.076; row 5, M5b), PAN density (-0.065; row 6, M6b) and lower proportion of VA with co-members (-0.074; row 8, M8b). Taken together, these results partially support Hypothesis 7.

Table 3.12 Weighted OLS Regression Models Predicting Each PAN Measure (n = 636)

		Female	Race (nonwhite)	Education		Religion			Age	Any Co-mem.	Intercept	R^2
				BA	> BA	Protestant	Catholic	other				
1. Personal Network Degree	M1a	NS	-.607***	NS	.415*	NS	NS	-.639*	NS		3.500***	.061
	M1b	NS	-.485**	NS	NS	NS	NS	-.746**	NS	.953***	3.045***	.159
2. VA Degree	M2a	NS	NS	.718***	.851***	.563**	.722**	NS	NS		1.486***	.062
	M2b	NS	.544*	.541**	.693**	NS	.600*	NS	NS	1.186***	.919***	.157
3. PAN Degree	M3a	NS	NS	.828**	1.266***	NS	NS	NS	NS		4.986***	.053
	M3b	NS	NS	.508*	.982***	NS	NS	NS	NS	2.139***	3.964***	.218
4. Personal Network Density	M4a	.094**	-.177***	.098*	.119**	NS	NS	NS	NS		.625***	.075
	M4b	.092**	-.158***	.076*	.099*	NS	NS	NS	NS	.148***	.554***	.110
5. Co-membership Density	M5a	NS	NS	NS	NS	NS	NS	NS	NS		.194**	.024
	M5b	-.045*	NS	NS	-.076***	NS	NS	NS	NS	.340***	NS	.393
6. PAN Density	M6a	NS	-.081*	NS	NS	NS	NS	NS	NS		.479***	.028
	M6b	NS	NS	NS	-.065*	NS	NS	NS	NS	.253***	.302***	.250
7. Proportion Co-member	M7a	NS	NS	NS	NS	.162**	NS	NS	NS		.247***	.040
	M7b	-.049*	NS	NS	NS	NS	NS	NS	NS	.610***	NS	.631
8. Proportion of VA with Co-members	M8a	NS	NS	NS	NS	.135*	NS	NS	NS		.318***	.024
	M8b	NS	NS	NS	-.074**	NS	NS	NS	NS	.622***	NS	.641
9. Average Co-membership	M9a	NS	NS	NS	NS	.261***	NS	.417*	NS		.238*	.034
	M9b	NS	NS	NS	NS	.105*	NS	NS	NS	.831***	NS	.348
10. Average Co-members in VA	M10a	NS	NS	NS	NS	NS	NS	NS	NS		.674*	.026
	M10b	NS	NS	NS	NS	NS	NS	NS	NS	1.121***	NS	.376
11. Concentration of Co-membership	M11a	NS	NS	NS	NS	NS	NS	NS	NS		NS	.017
	M11b	NS	NS	NS	NS	NS	NS	NS	NS	.467***	NS	.118
12. Concentration of Alters in VA	M12a	NS	NS	NS	NS	NS	NS	NS	NS		NS	.047
	M12b	NS	NS	NS	NS	NS	NS	NS	NS	1.163***	NS	.155
13. Fraction in the Largest Component	M13a	NS	-.081**	NS	NS	NS	NS	NS	NS		.723***	.038
	M13b	NS	-.051*	NS	NS	NS	NS	NS	NS	.236***	.610***	.300
14. Fraction in the Largest Bicomponent	M14a	NS	-.111**	NS	NS	NS	NS	NS	NS		.577***	.043
	M14b	NS	-.084**	NS	NS	NS	NS	NS	NS	.211***	.476***	.181

Note: Each major row presents the significant coefficients for each set of models predicting the PAN measures.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
NS Nonsignificant coefficient

Although more highly educated egos have larger expected PANs, their personal networks are expected to be denser than those of less-educated egos; there are no significant educational differences when predicting either PAN cohesion measure. When controlling for any co-membership, however, the most highly educated egos, compared to egos with the lowest educational category (less than a bachelor's), have less densely connected PANs and fewer shared memberships across voluntary associations. This suggests that, once controlling for the presence of co-membership ties, the PANs of highly educated egos spread further but are more sparsely knit, partially supporting Hypothesis 7.

While highly educated individuals have broader spread networks, their network connectivity and overlap in personal and associational ties do not differ. The lack of differences in PAN cohesiveness is particularly striking, as we may expect that more highly educated individuals may draw on more divergent actors in their network, creating less cohesive and more diffuse networks. I find, however, that these distinctions do not hold when incorporating personal and associational ties together. This may be due to highly educated egos acting as the "bridges" in the network and therefore having a larger number of shared co-membership ties. These distinctions cannot be made without exploring the relational dynamics in more detail, differentiating the types of alters egos are tied to (see Chapter 4).

When we switch the focus to religion, we see that Hypothesis 8 is partially supported, where network size variables vary, but density and cohesion measures are not significantly different across groups. Compared to religiously nonaffiliated egos, only those affiliated with "other" religions vary in personal network degree, where their personal networks are expected to be -0.746 members smaller on average (M1b). Voluntary association degree, however, is expected to be higher among Protestant and Catholic egos compared to religiously nonaffiliated egos: 0.563 and 0.722, respectively (see Table 3.12). However, once controlling for co-membership ties, Protestant egos do not differ in their voluntary association affiliations.

Table 3.13 F-tests Comparing Ego-level Characteristics with Two or More Categories

	Education [a]		**Religion** [b]	
	Model A	Model B	Model A	Model B
	F-value	F-value	F-value	F-value
1. Personal Network Degree	.284	1.97	2.81*	3.18*
2. Voluntary Association Degree	10.79***	7.47***	3.09*	2.08
3. PAN Degree	10.02***	6.33**	1.45	.62
4. Personal Network Density	5.68**	3.64*	1.68	1.10
5. Co-membership Density	.92	5.69**	3.40*	2.45
6. PAN Density	.77	3.60*	1.97	.79
7. Proportion Co-member	2.91	.29	4.24**	1.69
8. Proportion of VA with Co-members	1.53	4.28*	2.63*	.35
9. Average Co-membership	1.18	.27	5.05**	2.35
10. Average Co-members in VA	.48	1.46	4.07**	3.34*
11. Concentration of Co-membership	2.42	1.00	.76	.60
12. Concentration of Alters in VA	1.62	1.89	5.73***	5.31**
13. Fraction in the Largest Component	.02	2.30	2.25	.86
14. Fraction in the Largest Bicomponent	.29	1.00	3.07*	2.30

Note: F-test indicates whether the coefficients for each category are jointly different from zero.
[a] The F-test for Education compares the coefficients between egos with a BA and those with higher than a BA.
[b] The F-test for Religion compares the coefficients between Protestant, Catholic, and other religiously affiliated egos.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additionally, net of all other demographic characteristics, nonaffiliated egos vary in neither their overall PAN size nor their cohesion. If we compare across religiously affiliated egos, however, there are clear differences between Protestant, Catholic, and “other” religion categories. Table 3.12 presents the F-statistic for both models, testing the joint differences between groups. Among religiously affiliated egos, significant group differences exist in their personal network degree, their average co-members in voluntary associations, and their concentration of alters in voluntary associations.

Across all models, age was not significantly associated with PAN structure or composition. Surprisingly, and counter to previous research, I find no age differences in the expected value of shared membership. This holds true across proportional composition, magnitude, and concentration co-membership measures when controlling for any co-membership and when operationalizing age in different ways (results not presented here).[17] Overall, across all models, there is no support for Hypothesis 9.

Finally, looking at the differences across egos with and without shared membership ties, I find overwhelming support for Hypothesis 4: egos with any co-membership ties will be associated with larger, denser, and more cohesive PANs compared to egos without any co-membership ties. Despite many of the PAN measures encapsulating co-membership ties, important distinctions still exist in measures that do not include co-membership ties in their operationalization—specifically, the degree measures. Overall, egos that share contexts with their alters are, on average, more socially integrated than egos with no co-membership ties. This finding highlights the need to capture more than personal ties within measures of social integration.

[17] A series of sensitivity analyses were run using different age permutations. These included the addition of a squared age term and the use of categorical age cutoffs to better truncate young, middle-aged, and older adults. No significant age effects were identified across any such permutations.

3.5 DISCUSSION

This chapter had two main goals specific to the PAN measures defined in Chapter 2. First, it aimed to describe the structural and compositional features of personal affiliation networks (PANs) to understand how the inclusion of more detailed tie types may influence patterns of social integration. Second, this chapter aimed to identify any individual characteristics that may predict structural and compositional differences of PANs. Using findings from previous research as a baseline, I sought to identify if, and when, demographic differences in social integration hold when using PAN measures. Below I summarize the main findings for each analysis and detail the broader implications of these findings.

3.5.1 Summary of Results Part I: The Distribution of PAN Measures and the Relationship between Them

After exploring the univariate distribution of personal affiliation network (PAN) measures and the bivariate relationship between the measures using the 2006 NVAS as a case study (Hypotheses 1–4), I found four important contributions (see Table 3.14 for a summary of Hypotheses 1–4). First, using the unique data structure of the NVAS, which contains both personal and associational ties of egos, I identified overlapping social contexts. The fact that 62% of egos share at least one membership with those who are core to their personal network confirms previous theories on social integration and the embeddedness of our social connections (Breiger 1974; Feld 1981; Mollenhorst 2008; Pescosolido and Rubin 2000; Simmel 1955). Many individuals are, in fact, members of the same voluntary associations as those with whom they are close personally. This is an important finding when considering how social integration operates, as personal and associational ties are not definitionally independent of each other.

Table 3.14 Summary Table of Results Part I: The Distribution of PAN Measures and the Relationship between Them (Hypotheses 1–4)

#	Hypothesis	Support
1	Personal network degree will be positively associated with voluntary association degree.	Support
2	Voluntary association degree and PAN degree will be negatively associated with personal network density and PAN cohesion measures.	Partial Support
3	Personal network density will be associated positively with co-membership density, PAN cohesion measures, and all co-membership-specific measures.	Support
4	Egos with any co-membership ties will be positively associated with personal network degree, voluntary association degree, and personal network density.	Support

Second, there are nuanced structural and compositional patterns that exist within PANs in the NVAS, particularly related to co-membership ties (i.e., alter-association ties). Although the majority of egos with the potential for shared memberships (having at least one alter and at least one voluntary association membership) have at least some levels of co-membership, I found that co-membership is more complex than can be depicted with a dichotomous indicator. Although previous research has utilized co-membership ties as a binary relation type (akin to friend, spouse, or kin) (McPherson et al. 2006), there is high variability in the proportional composition, magnitude, and concentration of co-membership ties across alters and voluntary associations. For example, the proportion of alters who are co-members (proportion co-member) varies: around 18% of egos have at least one shared membership with every alter in their core discussion network, and nearly

40% (0.39) of egos share membership with at least half of their alters. This suggests that although co-membership within PAN exists across alters, there are more distinctions than a dichotomous indicator can capture.

Third, voluntary associations and personal networks operate in differing ways within an individual's PAN, but patterns of social integration are still maintained. For example, personal network degree—an indicator of individual social integration—is positively correlated with voluntary associations, and the density of personal networks is positively correlated with all co-membership-specific measures. These linear relationships suggest that the more socially integrated an individual is interpersonally, the more integrated they will be to voluntary associations—confirming Hypothesis 1 and Hypothesis 3 (see Table 3.12 for summary of hypotheses). At the same time, however, larger PANs cannot definitionally guarantee greater social connectivity. For example, for voluntary associations, a negative linear relationship exists between the number of voluntary association memberships, co-membership density, PAN density, and both PAN cohesion measures. As more organizational ties develop, more possible ties exist. As a result, co-membership ties are more diffuse, and the overall PAN is less dense. Personal networks remain salient spaces in the immediate social environment of individuals. These findings, taken together, partially confirm Hypothesis 2.

Fourth, there are significant structural differences between egos that share co-memberships with alters and voluntary associations and egos with no co-membership ties, thus confirming Hypothesis 4. Definitionally, the co-membership specific measures (co-membership density, proportional composition, magnitude of co-membership, and concentration of co-memberships) are different across groups, as egos without any co-membership (alter-association ties) have values of "0" for each above measure. For the measures that contain either alter-alter ties alone (personal network degree and personal network size) or both alter-alter and alter-association ties (PAN degree, PAN density, and PAN cohesion), significant differences exist across the two groups of egos.

3.5.2 Summary of Results Part II: Ego Demographic Correlates of PAN Measures

I note three important findings when exploring ego demographic correlates and their association with PAN measures. Table 3.15 displays a summary of Hypotheses 5 through 9 and corresponding results. As a reminder, these hypotheses were drawn from previous personal network and voluntary association participation literatures that use simple social integration measures. Using this literature as a baseline, I detail where PAN measures parallel findings from the simpler measures and where they differ.

First, PAN structure does not necessarily show the expected differences across egos based on demographic characteristics that are noted in previous studies. Rather, once associational ties are incorporated within the social environment of egos, more nuanced patterns exist. For example, we do not see the stark age differences expected in associational and personal ties across egos. Alternatively, even net of co-membership ties, personal network differences are maintained across sex: female egos are expected to have denser personal networks than males.

Co-membership measures, however, are not significantly different based on gender. While personal ties demonstrate gendered differences in social integration, once alter-association ties are incorporated into the measures, the gendered differences wash out. A likely explanation is the supplemental role that voluntary associations play, potentially acting as a substitute for other types of integrating ties. For example, although men have a lower personal network density, their co-membership ties may supplement their overall PAN connectivity and cohesion—an important point that would be missed without PAN measures. Incorporating other nuanced ties highlights the complexities of our social worlds, and thus it is important to use more precise measures of social integration. Future studies, however, should identify which, and to what extent associational ties supplement for personal ties.

The second major finding is specific to the few significant differences seen in the co-membership measures across demographic groups. While there are consistencies in demographic differences for the simpler, more commonly used measures of social integration (personal network degree, voluntary association degree, and personal network density), the same patterns do not hold when alter-association ties are incorporated. These nonsignificant findings can be explained by the role individuals to whom we are connected play in our social integration. That is, while there are few ego-specific characteristics that predict the overlap between personal and associational spaces, the ties that bridge these two spaces may be most influential in the overall structure of PANs. To better understand the nuances associated with social integration, therefore, the characteristics binding alters ought to be explored more deeply.

Table 3.15 Summary Table of Results Part II: The Ego Demographic Correlates of PAN Measures (Hypotheses 5–9)

#	Hypothesis	Support
5	Women will have a higher proportion, magnitude, and concentration of co-membership ties compared to men.	No Support
6	White egos, compared to nonwhite egos, will have larger but less dense PANs.	Partial Support
7	More highly educated egos are expected to have larger but less dense and less cohesive PANs than less-educated egos.	No Support
8	Religiously affiliated egos will have larger, more dense, and more cohesive PANs than nonaffiliated egos.	Partial Support
9	Older egos will have a higher proportion, magnitude, and concentration of co-membership ties compared to younger egos.	No Support

The third important contribution of these findings related to the co-membership characteristics of PANs. While many PAN measures incorporate co-membership (i.e., alter-association ties), even controlling for this variation I find significant differences across demographic groups, albeit varied by PAN measure. Still, the size and interconnectivity of PANs vary across egos with any co-membership (i.e., overlap in social spaces). The co-membership characteristics of PANs highlight the role of social integration: more social ties overall can lead to greater opportunity.

These findings provide important insights into how individual outcomes are associated with social integration. Pairing the demographic correlates associated with social integration for personal and associational ties with the influence that social integration has for individual outcomes (e.g., health, well-being, and social support) allows us to see how social integration is impacted when extending beyond personal ties or affiliation memberships alone. Because previous literature has focused on narrower measures of social integration, we may have been missing key network characteristics that amplify or dampen disparities across social groups associated with network-related indicators of well-being.

3.6 CONCLUSION

While typical personal network studies use measures of social integration, the measures are simple and miss important aspects of social life. Herein lies the need to reexamine previous findings with more precise measures of social integration. It is necessary not only to explore structural and compositional features of personal networks simultaneously, but also to reexamine how these compound integration measures may operate differentially across individuals. Toward that end, this chapter (1) described the structural and compositional features of personal affiliation networks and (2) identified individual characteristics that may predict structural and compositional differences of PANs.

The latter goal of this chapter holds particular importance for researchers and policy makers interested in understanding social dynamics related to personal and organizational integration—both at personal and organizational levels. Given past literature identifying personal network measures as proxies for social integration and their influence on outcomes like occupational success, mental health, and social support (Cornwell and Dokshin 2014; Davis et al. 2006; Fiori, Antonucci, and Cortina 2006; Verdery and Campbell 2019), illuminating individual characteristics that may predict structural and compositional differences of PANs may also shed light on the mechanisms through which disparities related to race, gender, and other demographic characteristics maintain and reproduce themselves.

Using a PAN data structure and measures with the 2006 NVAS as a case study, these analyses highlight the role that personal and associational ties have in binding the immediate social environments of individuals. I find that there is a high level of overlap between people's personal and associational ties, with nearly one-third of respondents having shared memberships in associations with their named alters. While I identified overlap between personal and associational spaces in PANs, the role of the ties that bridge personal and associational spaces (i.e., co-membership ties) need to be emphasized in future research. Once personal and associational ties are accounted for, we need to ask for whom, and in what ways, personal and associational ties influence social integration. I find that associational ties may supplement for personal ties, which may be important for researchers and policy makers concerned about community engagement and social capital as a means of increasing social integration. As group differences wash out with the inclusion of co-membership ties (alter-association ties), knowing the role that associational ties have on social integration (and particularly their bridging capacities) can inform research on social capital, social support, and other social integration correlates.

Additionally, the role that personal, associational, and co-membership ties have in integrating PANs introduces important considerations for individual-level outcomes. For changes that may occur in network structure and composition (either from a specific event or over time), for example, knowing the level of interconnections between personal and associational ties may help minimize, better target, or more effectively explain where fissures in social integration happen and how they will affect individuals. The consequences of changes to network structure, for instance, may be larger for individuals that share multiple types of social ties.

Using the COVID-19 pandemic as an example, there is no better time to account for more detailed tie types in order to improve researchers' and policy makers' understanding of how social integration operates. While this study does not measure tie loss or the COVID-19 pandemic specifically, it does provide important considerations for (1) understanding how social integration is patterned using a more detailed tie structure (incorporating personal and associational ties), (2) describing the differences in PAN social integration across demographic characteristics, and (3) developing possible measures useful to researchers when connecting personal and associational ties. Furthermore, before now, no studies would be able to tie personal and association ties together directly, nor were there the necessary tools to understand the implications of such ties.

This chapter cannot, however, identify *who* plays a role in integrating PANs. The lack of ego-level demographic differences for the co-membership specific measures indicates that compositional characteristics specific to the alters that bridge personal and associational spaces (i.e., alters with co-membership ties to the voluntary associations of egos) may explain these structural differences more effectively. Those that compose an individual's immediate social environment and their relationships may be more telling than the individual's demographic characteristics alone. Thus, future research should explore not only who is socially integrated but also which named alters have an influence on social integration, especially when accounting for personal and associational ties in PANs. In the next chapter, I take up this need directly by (1) calculating the relative influence that alters have on social integration (specific to the PAN data structure) and (2) identifying the demographic and tie characteristics associated with alters who have higher levels of influence.

CHAPTER 4 WHO INTEGRATES PERSONAL AFFILIATION NETWORKS (PAN)? ALTERS AS SOCIAL INTEGRATERS

4.1 INTRODUCTION

Social integration is known to impact many individual outcomes, from health and well-being to social influence and access to social resources (Agneessens et al. 2006; Berkman 2000; Berkman and Glass 2000; Friedkin 2004; van der Horst and Coffé 2011). At a foundational level, the social connections that individuals have structures their immediate social environment (McPherson et al. 2006; Perry et al. 2018; Smith et al. 2014). Ego networks are often employed to explore individual social integration, where both ego network composition (i.e., who our alters are) and ego network structure (i.e., how our alters are connected) are used to capture the dependencies between larger network features and the dyadic ties constructing the network (McCarty 2002; Vacca 2019; Wellman and Frank 2017; Wellman and Wortley 1990). Other types of social ties, such as membership in voluntary associations, also integrate individuals (Bonikowski and McPherson 2007; Booth and Babchuk 1969; Chua and Erickson 2016; Feld 1981; Pescosolido and Rubin 2000). In Chapter 2, I used personal networks and voluntary association memberships to construct personal affiliation networks (PANs). I constructed this data structure as a way to more precisely, and explicitly, incorporate the personal and associational ties of individuals in a single, interconnected social network.

In Chapter 3, I identified (1) how personal affiliation network (PAN) structure is distributed across egos and (2) how PAN structure is associated with ego demographic characteristics. Furthermore, Chapter 3 identified important dependencies that exist between personal and associational spaces that can be used to better capture individual social integration. While the personal network degree and personal network density measures support differences across demographic groups as found in previous studies, the same demographic associations do not hold when using more detailed social integration measures. Although the previous chapter explores the ego-level features associated with ties to personal and associational spaces shared by an ego and core network members, it can identify neither *which* core members are bridging personal and associational environments nor salient alter-level characteristics that foster social integration.

Therefore, this chapter transitions the focus from egos to the alters that constitute PANs, using three types of alter characteristics to identify which network members are most influential in shaping the social integration of egos: homophily characteristics, tie characteristics (type and strength), and co-membership characteristics. I use a subset of 393 egos from the 2006 National Voluntary Association Study (NVAS) who share at least one common voluntary association membership with a network member (i.e., they have at least one co-membership tie). I empirically identify which alters have the greatest influence on an ego's PAN structure, where influence is defined as how much the network structure would change if all ties to a given alter were dropped. Using the 1,478 nominated alters of the 393 egos, I predict the level of influence alters have on the PAN structure, focusing on seven of the PAN measures defined in the second chapter: personal network density, co-membership density, PAN density, proportion co-member, proportion of voluntary associations with co-members, fraction in the largest component, and fraction in the largest bicomponent.

This study generates fresh insights into how social connections can be used to measure the social integration of individuals. Identifying consequential alters in a network can inform how changes to ties in an ego network may influence individuals. For instance, effect of the loss or creation of a tie may depend on who the tie is to. If, for example, an alter is a spouse with many shared personal and associational ties and this relationship is broken, the overall network structure may be shattered. Alternatively, if an alter does not share ties to other persons or associations in the network, losing such a tie may be less consequential. Current research, however, misses these important nuances related not only to how ego networks are connected personally and associatively, but to which ties act as integrators within these networks. To address these shortcomings, I extend previous research by focusing on personal and associational ties rather than on personal network ties alone.

This chapter begins by briefly summarizing past work on ego network structure and composition (Section 4.2). Using extant research, I develop hypotheses centered around three alter-level characteristics (homophily, ties, and co-memberships) that may influence a PAN structure specifically (Section 4.3). I then describe the data and introduce a series of analyses aimed at identifying influential alters (Section 4.4). Using univariate, bivariate, and multivariate statistics, I predict the seven alter influence scores as a function of the homophily, tie, and co-membership characteristics of alters (Section 4.5). I end by discussing the findings and suggest important considerations for social integration focusing on alters, the ties that bind our social worlds (Section 4.6).

4.2 BACKGROUND

4.2.1 Dyadic Influence: The Role of Alters in Shaping Ego Social Integration

A long literature has used information about alter characteristics to understand the composition of ego networks (Agneessens et al. 2006; Fiorillo and Sabatini 2011; McPherson et al. 2001; Smith et al. 2014). Features such as homophily, role relations, and tie strength have been identified as predicting the structural features of networks. Using these three features, I extend previous research by exploring how the characteristics of ego-alter relationships may influence social integration. Moreover, I draw on these features when developing hypotheses about the role that alters have on integrating ego networks using a PAN approach.

4.2.1.1 Homophily Characteristics

Homophily is an organizing principle of society often characterized by the phrase “birds of a feather flock together” (McPherson et al. 2001). Developed by McPherson et al. (2001), homophily is the tendency for an individual to have more social connections to similar individuals than to dissimilar individuals. Often operationalized as a match or mismatch on key sociodemographic variables (e.g., sex, race, education) (Smith et al. 2014), homophily can also be applied to other social behaviors. Previous studies, for example, have used the principle of homophily to explore drinking and smoking behaviors, often centered around youth (Goodreau, Kitts, and Morris 2009; Haynie 2001; Schaefer, Haas, and Bishop 2012). Overall, homophily operates as a strong indicator for social connectivity and is commonly used to assess individuals’ likely social ties.

Previous research has emphasized two important features of homophily: (1) homophily is strong in ego networks, where egos share many common attributes with those to whom they are personally connected, and (2) homophilous ties have greater influence on the behaviors of egos than dissimilar ties (Kalmijn and Vermunt 2007; Lee, Kim, and Piercy 2019; Louch 2000; McPherson, Lynn Smith-Lovin, et al. 2001). Alters that are homophilous, therefore, may be more likely to share common association memberships with egos and to share memberships in a wider set of associations than non-homophilous alters. Thus, homophilous alters can be expected to have more ties and more influence on the PAN structure compared to dissimilar alters.

> **Hypothesis 1:** Alters that are homophilous on demographic attributes will have more influence for all PAN measures compared to dissimilar alters.

4.2.1.2 Tie Characteristics: Tie Type

The types of people that individuals are tied to, frequently referred to role relations, have been commonly explored in ego network research. Previous research has highlighted the importance of role types, often categorized as kin or non-kin, and their influence on social integration (Agneessens et al. 2006; Fiorillo and Sabatini 2011; Mandel 1983; Rözer, Mollenhorst, and Poortman 2016; Smith and Christakis 2008). Role relations vary in their social influence, social support, and access to resources (Agneessens et al. 2006). Specific role relations, such as spousal ties, have been used to identify how particular alters structure an ego's network (Cornwell 2012; Uchino et al. 2013). Cornwell (2012), for example, looks at the association between overlap in spousal networks and social support, finding that social support is contingent on the connectedness of a spouse's network. Furthermore, varying types of alters may differentially influence social network connectivity. For example, kin ties may not influence the ego networks of business partners in the same way that friends might (Davis et al. 2006; Renzulli and Aldrich 2005).

Therefore, I propose that different types of alters will differentially influence an ego's social integration. For instance, because spouses have strong, salient ties known to overlap with their partner's personal network, I expect that they will also have a large influence within PANs. Additionally, previous research has established that personal networks contain a high level of kin ties. Thus, after spouses, I expect other types of kin to influence the personal ties and the combined personal and associational ties within a PAN more than non-kin alters, as personal networks have more kin ties than other types of ties (i.e., to associations).

> **Hypothesis 2:** Alters who are spouses will be more influential across all PAN measures compared to other kin and non-kin alters.

> **Hypothesis 3:** After spouses, other kin alters will have more influence on the PAN measures that are isolated to personal ties (personal network density) compared to non-kin alters.

> **Hypotheses 4:** Non-kin alters will have more influence on the co-membership-specific PAN measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members) compared to other kin alters.

4.2.1.3 Tie Characteristics: Tie Strength

Ego network research often examines the strength (or quality) of the ties binding egos and alters. There are many ways tie strength can be captured. It is often measured as the length of the relationship, its frequency of interaction, or its multiplexity (i.e., the extent to which ties having multiple role sets, like a friend who is also a neighbor) (Agneessens and Skvoretz 2012; Bianchi and Vohs 2016; Comulada, Muth, and Latkin 2012; Cornwell and Waite 2009; Dissing et al. 2018; Mollenhorst, Völker, and Flap 2008). Over time, ties strengthen, creating stronger and more durable relationships that are harder to break. Similarly, frequent interactions with alters strengthen relationships by helping the individuals better understand each other's support needs, from companionship to help in a difficult time.

Having long-lasting relationships and frequently activated ties, therefore, has implications for social influence and broader social connectivity. Given these qualities, I expect alters that have been tied to egos for longer to be more influential for an ego's overall integration. Additionally, because frequent interactions increase network connectivity, I expect the alters that an ego interacts with regularly will have more influence on their network structure, regardless of personal or associational ties.

> **Hypothesis 5:** Alters that have been tied to egos for a longer time will have more influence on all PAN measures, but less for co-membership specific measures, compared to more newly developed ties.

> **Hypothesis 6:** Alters that more frequently interact with an ego will have more influence on all PAN measures compared to alters where interaction is less frequent.

4.2.2 Voluntary Associations, Ties, and Alter Influence

Voluntary associations have been found to be integrating but also segregating—producing more homogenous rather than more diverse social spaces

(Booth and Babchuk 1969; McPherson and Smith-Lovin 1986; Popielarz and McPherson 1995). Some scholars have found that, from the integrating perspective, voluntary associations offer more connections to a more diverse sets of ties (Babchuk and Edwards 1965; Putnam 2000a; Wellman 2000). For example, many studies have identified that individuals have larger and more diverse networks when they belong to one or more voluntary associations (McPherson et al. 1992; Popielarz 1999a; Putnam 2000a; Rotolo 2000; Wilson and Musick 1997). Other scholars, however, have found voluntary associations as segregating (Bonikowski and McPherson 2007; McPherson and Rotolo 1996; McPherson and Smith-Lovin 1987; Popielarz and McPherson 1995). The segregating features of voluntary associations may reinforce principles of homophily, where memberships to voluntary associations are shared with those with whom individuals share other common ties (McPherson et al. 1992; Popielarz and McPherson 1995). If this is the case, voluntary association memberships may not increase network diversity.

Previous research has identified the role of friends in the voluntary association participation of individuals, where individuals are more likely to participate in voluntary associations (organizations) if a friend is also participating (McPherson et al. 1992; Popielarz and McPherson 1995). The consequences of this overlap between personal and associational participation, however, has not been explored in previous research. Additionally, it is unknown how alters influence the broader connectivity of one's social network. Because previous research has not examined the direct overlap between personal and associational networks, no clearly defined relationships have been established that identify the influence that alters have on an ego's ties to voluntary associations.

Alter tie characteristics specific to voluntary associations may influence an ego's social integration (especially within the context of PANs). Because voluntary associations are less kin-centered than some other social spaces and can operate as locations fostering tie formation, I can anticipate how alters may be particularly influential to social integration. For example, I expect non-kin alters (e.g., friends) to have greater influence on bridging personal and associational ties. This expectation is detailed in Hypothesis 4 above. Additionally, voluntary associations can form ties that are non-kin specific. If, for example, the personal tie to an alter was formed within an association, that alter's influence may be greater than if the personal tie was formed elsewhere. Therefore, I expect that alters who met an ego at an association may have a stronger influence on the integration tying together that ego's personal and associational ties.

Additionally, the number of an alter's co-membership ties may indicate their larger social connectivity: the more social connections an alter has to the same associations as an ego, the more integrated they will be within the larger PAN, including to personal ties. Therefore, I expect alters with more co-membership ties to have greater influence on an ego's integration, both within personal networks and within PANs.

> **Hypothesis 7:** Alters that an ego met in a voluntary association will have more influence on the co-membership-specific PAN measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members) compared to alters that the ego did not meet in an association.

> **Hypothesis 8:** Alters with more co-membership ties will have more influence on PAN measures isolated to personal ties (personal network density) or combined personal and associational ties (PAN density, fraction in the largest component,

and fraction in the largest bicomponent) than alters with no co-membership ties.[18]

Table 4.1 Summary Table of Hypotheses for Homophily, Tie, and Co-membership Characteristics Associated with Alter Influence on PAN Structure

#	Hypothesis
	Homophily Characteristics
1	Alters that are homophilous on demographic attributes will have more influence for all PAN measures compared to dissimilar alters.
	Tie Characteristics
	Tie Type
2	Alters who are spouses will be more influential across all PAN measures compared to other kin and non-kin alters.
3	After spouses, other kin alters will have more influence on the PAN measures that are isolated to personal ties compared to non-kin alters.
4	Non-kin alters will have more influence on the co-membership-specific PAN measures compared to other kin alters.
	Tie Strength
5	Alters that have been tied to egos for a longer time will have more influence on all PAN measures, but less for co-membership specific measures, compared to more newly developed ties.
6	Alters that more frequently interact with an ego will have more influence on all PAN measures compared to alters where interaction is less frequent.
	Co-membership Characteristics
7	Alters that an ego met in a voluntary association will have more influence on the co-membership-specific PAN measures compared to alters that the ego did not meet in an association.
8	Alters with co-membership ties will have more influence on PAN measures isolated to personal ties or combined personal and associational ties than alters with no co-membership ties.

4.2.3 The Current Study

While compositional features, such as tie characteristics, have been used to predict structural features of ego networks, little research has identified how

[18] These comparisons are specific to PAN measures that have either only personal ties or the combination of personal and co-membership ties, as the co-membership-specific measures are definitionally influenced by co-membership ties.

compositional features may be associated with social integration overall. Therefore, in this study, relying on a PAN structure, I explore how alter-level characteristics may be tied to the personal and associational features of the network. I identify how much influence specific alters have on integrating PANs, where influence captures how much the network structure would change if all ties to a given alter were dropped. Therefore, this study extends previous research by directly exploring the level of influence that alters have on the structure of ego's social environments, specifically their ties to voluntary associations. Table 4.1 presents all eight hypotheses related to homophily, tie type and strength, and co-membership characteristics.

4.3 DATA AND METHODS

4.3.1 Data: The 2006 National Voluntary Association Study (NVAS)

The 2006 National Voluntary Association Study (NVAS) is a re-interview sample of individuals who completed the 2004 General Social Survey (GSS) module on Voluntary Associations and Networks. The NVAS was collected to better understand the role of voluntary associations in individuals' lives. Its sample was drawn from a sampling frame of 2004 GSS respondents stratified by voluntary experience—split by those with and without voluntary association membership. Through telephone interviews, collected by NORC, the NVAS was completed by 860 individuals yielding nearly a 60% response rate. Many of the same survey instruments used in the 2004 GSS module were also included in the 2006 NVAS re-interview survey, including the personal networks and voluntary association memberships of respondents.

For these analyses, I use primarily the first two sections of the survey focused on individuals' group affiliation and individual social networks. The NVAS gathers information on the voluntary association participation of respondents (group affiliation) as well as detailed information about individual respondents' immediate social worlds (social networks). Therefore, it is a particularly useful data source for exploring how the personal and associational spaces of individuals operate, as it incorporates the three main types of information necessary for constructing personal affiliation networks (PANs): respondents' voluntary association memberships, their egocentric networks, and their shared memberships.

Voluntary association memberships are measured based on 16 association types including union membership, church, and sports clubs. A ego network name generator asked "who are the people with whom you discussed matters important to you?" (see Marsden 1987 and McPherson et al. 2006), permitting respondents to nominate up to five core network members (i.e., alters). A detailed name interpreter was used to gather typical information about each alter, including sociodemographic characteristics and tie-specific characteristics. Additionally, the NVAS included detailed information on the co-membership ties that each alter shares with the associations of egos within the name interpreter. See Chapter 3, Section 3.3.2 for a detailed description of each NVAS component.

These data are unique because they measure and include social ties beyond a personal network, specifically identifying direct links between individual alters and associations. The shared co-membership of alters to an ego's voluntary associations are identified by each alter j tied to voluntary association k. These data capture social integration from a multi-dimensional and multi-embedded perspective missing in previous studies. Additionally, when looking at the role of alters specifically, the NVAS provides the alter-level specificity to determine influence based on the homophily, tie, and co-membership characteristics that most influence PAN structure and social integration.

4.3.1.1 Analytic Sample

For the analyses presented in this chapter, I focus only on egos that have at least one co-membership in their personal affiliation networks (PANs). As a result, the sample of egos are subset from 636 to 393.[19] Given that the goal of this chapter is to explore the influence that alters have in integrating individuals, I construct a nested dataset of nominated alters nested within egos. Across the 393 egos, there are 1,478 nominated alters, and all analyses predict alter-level outcome variables nested within egos.

4.3.2 Dependent Variables: Alter Influence Scores

In these analyses, I explore the effect that individual alters have on personal affiliation network (PAN) structure. I focus specifically on seven of the PAN measures defined in Chapter 2: personal network density, co-membership density, PAN density, proportion co-member, proportion of voluntary associations with co-members, fraction in the largest component, and fraction in the largest bicomponent. Defined in Equation 4.1, each influence measure captures the percentage decrease in the observed PAN measure when all ties from alter *j* are removed from the PAN. Alter influence_{ij} is a level-1 (or alter-level) variable that is nested within egos *i*, where each

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[19] The sample of 636 references the egos that were analyzed in Chapter 3. Specifically, the 636 egos are a subpopulation of the full NVAS limited to those that have the possibility of co-membership ties within their PAN—that is, they have at least one nominated alter and one voluntary association membership. Three individuals that had the possibility of co-membership were dropped from the sample, as they were missing the weight variable accounting for their probability of selection.

influence measure could range from 0 to 100 and captures the relative influence between ego *i* and alter *j*.

$$alter\ influence_{ij} = \left(\left(\frac{observed_i - new_{ij}}{observed_i}\right) * 100\right) \tag{4.1}$$

$Observed_i$ is the ego-level PAN measure of the complete PAN network, with no alter ties removed, and is held constant for all calculations of alters nested within an ego. New_{ij} is the recalculated PAN measure with all ties to alter *j* removed. A new_{ij} measure is calculated for each alter *j* of ego *i*.

Two main steps are taken to construct each recalculated PAN measure (new_{ij}). Step 1 removes all alter *ij* ties from the PAN. Step 2 then recalculates each PAN measure (*x*) with the removed alter *ij* ties. This two-step process is repeated k times, where k = {1,…,n} and n is equal to the ego's alter degree. Importantly, all influence scores are calculated based on the removal of ties (i.e., links between alters and voluntary associations), not the removal of nodes (i.e., the alters or voluntary associations). In order to directly compare the network structure when alters are removed, the same possible structural features of the PAN need to be retained. Therefore, an alter's influence on the social integration of ego *i* is defined based on the ties that bind the PAN.

More generally, the alter influence score shows how much the new PAN measure (with all ties from alter *j* removed) differs from the observed PAN measure (calculated with all alter ties included). The percentage influence is relative to the observed empirical value, which makes the influence scores comparable across egos. Each influence score, therefore, can be interpreted in the same way, where alter influence is “0” when there is no resulting change in the network measure with removal of alter *j* tie(s). This would occur if an alter, for example, has no ties to other nodes in the network. On the opposite end of the spectrum, if an alter had many ties to other nodes in the network, they would have a high level of influence: the removal of their nodes from the network would highly alter the structural properties of the PAN.

As noted above, I rely for these analyses on only seven of the PAN measures defined in the previous chapters. I made two important considerations when selecting the PAN measures. The first consideration focused on the network degree measures. Because I am interested in the influence that a given alter has on an ego, the size of the PAN is held constant, and only ties between nodes are taken out when calculating the influence each alter has on the network’s structure. Given that none of the nodes (neither alters nor voluntary associations) are removed from the PAN in the calculation, alters have no influence on the size of the network. Therefore, no influence measures are calculated for the network degree measures, as they are constant across alters. To control for variation in PAN size, however, I include a centered measure of PAN degree in every model.

The second consideration pertains to the co-membership-specific measures. There are definitional dependencies between the proportion co-member measures and magnitude of co-membership measures (average co-membership and average co-members in voluntary associations). Each of these measures is isolated to co-membership ties (alter-association ties), and at the alter level, alters would have the same influence across all co-membership-specific measures. Therefore, I incorporate only one set of the co-membership measures within these analyses: proportional composition, specifically the proportion co-member and the proportion of voluntary associations with co-members.

4.3.3 Independent Measures

Three sets of independent variables are used within these analyses: homophily, role relation characteristics, and alter co-membership characteristics. Each set of independent variables is at the alter level (level-1) and is specific to each alter, nested within egos. In addition, every model includes controls for alter-level (level-1) demographic characteristics and ego-level (level-2) PAN size. Below, I detail each set of key independent variables and the additional control measures included in all analyses.

4.3.3.1 Homophily Characteristics

Homophily is an organizing principle of many social systems that captures the general tendency for people with similar attributes to be more highly connected (at least at a higher rate) than individuals with dissimilar attributes (Marsden 1987; McPherson, Lynn Smith-Lovin, et al. 2001; McPherson et al. 2006; Smith et al. 2014). Five homophily measures are included in the models to control for common demographic homogenizing characteristics (see Smith et al. 2014, for example). Specifically, I measure the similarity of alters to egos based on sociodemographic covariates sex, race, education, religion, and age. The sex, race, education, and religion homophily measures are dichotomous indicators that identify if there is match on the specific characteristic. Dissimilarity, where the alter and ego do not share the same identity, is indicated by “0,” whereas “1” indicates matching on the identity. Additionally, a homophily measure for age is included; this measure is operationalized as the absolute difference in age, where the variation is in the distance above or below the ego's age.

4.3.3.2 Tie Characteristics: Tie Type and Tie Strength

Three main variables are included to capture important characteristics about the relationship between each ego and alter. The first role relation measure is specific to the role type between each alter-ego tie: spouse, other kin, or non-kin (reference). In addition to the specific types of ties, two covariates are included to capture the strength of ties—the length of relationship and the frequency of interaction. Length of relationship is a three-category variable that captures the length of time that an ego and alter have known each other. The length of relationship is defined as less than 5 years, 5 to 10 years, or 10 or more years. Additionally, the frequency of interaction between ego and alter is measured temporally as "about once a month or less" (reference), "about once a week," or "almost daily."

4.3.3.3 Co-membership Characteristics

The final key independent variables are specific to memberships that egos share with alters. These covariates provide context for where the relationship was formed and account for alters' level of embeddedness in the PAN. To capture whether the relationship was started in the voluntary association, I include an indicator where "0" represents that the tie was not formed through a voluntary association and "1" represents a tie that was formed within an association. From a social integration perspective, having met in an association may indicate substantial overlap between an individual's personal and associational spaces. Level of co-membership is a three-category variable that captures the extent of co-membership ties that an alter shares with an individual; it is operationalized as alters who are not co-members (reference), alters who have a single co-membership, or alters with two or more co-membership ties.

4.3.3.4 Control Variables

I control for alter-level demographic characteristics matching all homophily measures and for an ego-level measure of network size. Specifically, I include alter gender, race, education, religion, and age as alter-level controls. Gender and race are both coded as dichotomous indicators—male (reference)/female and white (reference)/non-white, respectively. Education is a three-category variable: less than a BA degree earned (reference), BA, and higher than BA. Religion is a four-category variable capturing religious affiliation measured as Protestant, Catholic, other, and nonaffiliated/unknown (reference). Age is a continuous variable with missing data imputed based on the sample mean. In addition to the alter-level characteristics included as covariates, I also control for the level-2 (ego) covariate PAN size. PAN degree is a continuous measure that is grand mean centered around the average PAN degree of all egos.

4.3.4 Analytic Strategy

To assess the level of influence each alter has on the social integration of an individual ego, I rely on univariate, bivariate, and multivariate statistical techniques to appropriately account for the nested nature of the NVAS, wherein ego and alters do not depend on each other. Rather, alters are nested within egos, and all analyses presented here account for such dependencies. First, using univariate statistics, I describe the sample, highlighting key ego and alter features, including the key independent variables. Second, I explore the bivariate relationship between relational characteristics (homophily, role relations, and co-membership) and each alter influence score with group mean t-tests, pairwise mean comparison for measures with more than two groups, and correlations for continuous measures. Third, I explore the multivariate relationship between homophily, tie, and co-membership characteristics when predicting alter-level influence.

When predicting each alter influence measure, certain measures required multilevel models and others required clustered OLS regression models. These decisions were made by testing the dependencies of the null random intercept models by accessing the intraclass correlation coefficient (ICC) of each null model. Table 4.1 displays the ICCs for each of the null random intercept models. The null model is defined in Equation 4.1, where the only random effect is on the intercept—means across egos—and no covariates are added to the model. β_0 is the intercept for all alters, and u_{oi} is the random intercept, which varies from ego to ego.

$$y_{ij} = \beta_0 + u_{oi} + e_{ij} \tag{4.2}$$

I use the ICCs as a test for identifying the appropriate statistical model to adequately account for the dependencies of the nested data structure. The ICC in a null random intercept model can be interpreted as the within-cluster correlation (Rabe-Hesketh and Skrondal 2008; Raudenbush and Bryk 2002), which ranges from 0 to 1, where higher correlations equate to higher within-cluster correlation. More generally, ICC determines the level of dependence due to cluster mean differences and highly influences model specification. The higher the ICC, the more likely OLS regression assumptions will be violated, as there is clear dependence between levels, where clusters ought not be ignored.

Using Table 4.2 as a guide, I employ multilevel modeling when predicting the personal network density, PAN density, fraction in the largest component, and fraction in the largest bicomponent measures, as their ICCs are moderate and require model specifications that account for the dependencies between egos and alters. For the influence measures of co-membership density, proportion co-member, and proportion of voluntary associations with co-members, I employ clustered linear regression models, as the ICCs are nearly 0.00 across each measure. For these three measures, therefore, a multilevel model is not needed. Rather, I employ clustered linear regression where standard errors are adjusted to account for the clustering of alters within egos.

Table 4.2 Intraclass Correlation (ICC) Null Random Intercept Models

	ICC	CI
Inf. Personal Network Density	.579	[.459,.691]
Inf. Co-membership Density	—	—
Inf. PAN Density	.306	[.176,.478]
Inf. Prop. Co-member	—	—
Inf. Prop. of VA with Co-members	—	—
Inf. Fraction in Largest Component	.260	[.144,.424]
Inf. Fraction in Largest Bicomponent	.200	[.060,.495]

For all multivariate models, I run two different models for each of the seven alter influence measures, all of which control for alter sociodemographic characteristics and the grand mean-centered PAN degree. The first model predicts each influence measure as a function of all three sets of alter characteristics: homophily (Hypothesis 1), tie type and strength (Hypotheses 2-6), and meeting at an association (Hypothesis 7). The second model adds the number of co-membership ties to control for the level of overlap a given alter has in bridging egos and associations (Hypothesis 8).

The two multilevel and clustered OLS regression models are defined below. Equations 4.3-4.4 define the multilevel models, and Equations 4.5-4.6 define the clustered OLS regression models.[20]

4.3.4.1 Multilevel Model Equations[21]

Model 1: Alter Influence ~ Homophily Characteristics + Ties Characteristics + Co-membership Characteristic (Met at Association)

$$\begin{aligned} alter\ influence_{ij} = \beta_0 + \beta_1 same\ sex_{ij} + \beta_2 same\ race_{ij} + \beta_3 same\ education_{ij} \\ +\beta_4 same\ religion_{ij} + \beta_5 age\ diff_{ij} + \beta_6 tie\ type_{ij} \\ +\beta_7 length\ of\ relationship_{ij} + \beta_8 interaction\ freq._{ij} \\ +\beta_9 met\ at\ assocation_{ij} \\ + u_{oi} + e_{ij} \end{aligned} \tag{4.3}$$

Model 2: Alter Influence ~ Homophily Characteristics + Tie Characteristics + Co-membership Characteristics

$$\begin{aligned} alter\ influence_{ij} = \beta_0 + \beta_1 same\ sex_{ij} + \beta_2 same\ race_{ij} + \beta_3 same\ education_{ij} \\ +\beta_4 same\ religion_{ij} + \beta_5 age\ diff_{ij} + \beta_6 tie\ type_{ij} \\ +\beta_7 length\ of\ relationship_{ij} + \beta_8 interaction\ freq._{ij} \\ +\beta_9 met\ at\ assocation_{ij} + \ \beta_{10} co - membership\ ties_{ij} \\ + u_{oi} + e_{ij} \end{aligned} \tag{4.4}$$

4.3.4.2 OLS Regression Equations with Clustered Standard Errors[22]

Model 1: Alter Influence ~ Homophily Characteristics + Ties Characteristics + Co-membership Characteristic (Met at Association)

[20] All models include the alter-level demographic controls (sex, race, education, religion, age) and the centered ego-level (level-1) PAN degree as a control.
[21] No control variables are included in the defined models.
[22] No control variables are included in the defined models.

$$alter\ influence_{ij} = \beta_0 + \beta_1 same\ sex_{ij} + \beta_2 same\ race_{ij} + \beta_3 same\ education_{ij} + \beta_4 same\ religion_{ij} + \beta_5 age\ diff_{ij} + \beta_6 tie\ type_{ij} + \beta_7 length\ of\ relationship_{ij} + \beta_8 interaction\ freq._{ij} + e_{ij} \quad (4.5)$$

<u>Model 2</u>**:** Alter Influence ~ Homophily Characteristics + Tie Characteristics + Co-membership Characteristics

$$alter\ influence_{ij} = \beta_0 + \beta_1 same\ sex_{ij} + \beta_2 same\ race_{ij} + \beta_3 same\ education_{ij} + \beta_4 same\ religion_{ij} + \beta_5 age\ diff_{ij} + \beta_6 tie\ type_{ij} + \beta_7 length\ of\ relationship_{ij} + \beta_8 interaction\ freq._{ij} + \beta_9 met\ at\ assocation_{ij} + \beta_{10} co - membership\ ties_{ij} + e_{ij} \quad (4.6)$$

4.3.4.3 Complex Survey Design Adjustments

All univariate, bivariate, and multivariate analyses were conducted in Stata version 16. I accounted for the complex nature of the survey data by using weights and strata. I used the svy estimation commands in Stata, specifically relying on the svy: package to adequately adjust standard errors taking into account the unequal probability of selection and clustering. For the multivariate models specifically, I employed either weighted multilevel generalized linear models (svy: meglm) using a gaussian distribution or weighted linear models with clustered standard errors (reg with [pweight =] and vce(cluster) specifications).

For the analyses using multilevel models, all weights are applied to the ego (level-2) covariates, as the probability of selection is only defined at the level of the individual. No staged design was employed among nominated alters; therefore, their probability of selection into the PAN is undefined. In the weighted linear regression models, I cluster the standard errors at the ego-level using ego-specific identifiers.

This type of clustering technique adjusts the standard errors to account for the nested data structure of alters within egos without employing a multilevel model.[23]

Table 4.3 Descriptive Statistics of Alter and PAN-level Controls

		%/Mean (SD)
Alter Characteristics		
Sex (Female)		52.32
Race (non-white)		22.21
Education		
	< BA	51.29
	BA	23.38
	> BA	25.33
Religion		
	Protestant	36.81
	Catholic	22.98
	Other	13.12
	Nonaffiliated/Unknown	27.09
Age		47.332 (15.587)
PAN Degree[1]		6.928 (2.394)
	N dyads	1,478
	N egos	393

[1] The non-centered distribution of PAN degree is displayed; however, all models incorporate the centered PAN degree measure.

4.4 RESULTS

4.4.1 Univariate Results

Table 4.3 displays the sociodemographic breakdown of alters across all egos. Of the alters, 52.32% are female and 22.21% are non-white; the average alter is 47.33 years old. Over 50% of alters have education of less than a bachelor's degree, and the remaining half or so of alters are relatively split between having a bachelor's

[23] For the three co-membership-specific PAN measures using OLS regressions with clustered standard errors (co-membership density, proportion co-member, and proportion of voluntary associations with co-members), as a robustness check, I ran additional analyses employing the multilevel approach used for the other four influence measures. There were no substantive differences between the OLS and HLM result. I relied on the HLM models for these three measures primarily because, although each model converged, the variance components could not be estimated. Therefore, for ease of interpretation I only present results of the OLS models for the three co-membership-specific alter PAN influence measures.

degree (23.38%) and higher than a bachelor's degree (25.33%). The majority of alters are identified as religiously affiliated: 36.81% identified as Protestant, 22.98% as Catholic, and an additional 13.12% affiliated with another type of religion. Over a quarter of alters (27.09%), however, were either identified as not religiously affiliated or their religious affiliation was unknown to the ego. Additionally, across the 393 egos with any co-membership ties, the average PAN degree is 6.928—including alters and voluntary associations.

Table 4.4 Descriptive Statistics of Key Independent Variables—Homophily, Tie, and Co-membership Characteristics of Alters

		%/Mean (SD)
Homophily Characteristics		
Same Sex		64.89
Same Race		88.89
Same Education		34.00
Same Religion		52.31
Abs. Difference in Age		11.81 (11.35)
Tie Characteristics		
Tie Type		
Role Relation		
	Non-kin	54.07
	Spouse	14.64
	Other Kin	31.29
Tie Strength		
Length of Relationship		
	< 5	24.30
	5-10	14.16
	10+	61.54
Interaction Frequency		
	~ Monthly	17.03
	~ Weekly	35.98
	~ Daily	46.98
Co-membership Characteristics		
Co-membership Ties		
	0	43.95
	1	44.95
	2+	11.10
Met at VA		20.49
	N dyads	1,478
	N egos	393

Focusing on key ego-alter tie characteristics, Table 4.4 presents the descriptive statistics for the homophily, tie type and strength, and co-membership characteristics of alters. High homophily exists for sex and race, where 64.89% of alters are the same sex and 88.89% are the same race as their nominating ego. Education, however, is a less salient homophily measure, as just over a third (34.00%) of alters match the education of their ego.[24] Religion homophily is relatively split with alters, where just over half (52.31%) of alters match their ego's religion. On average, alters tend to have an almost 12-year age gap between themselves and their egos (11.81).

Next, when looking at the types of alters associated with egos, I find that 54.07% of alters are non-kin (e.g., friends, co-workers, etc.), 14.64% are spouses, and the remaining 31% are other kin (e.g., parents, children, siblings). Overall, the ties between egos and alters are strong: the majority of alters have had a relationship with the ego for ten years or more (61.54%). About a quarter of alters are newer to the ego's PAN: 24.30% of alters have had a close relationship to the ego for less than five years. The remaining 14.16% of alters have an intermediate-length relationship with egos (five to ten years long). Interaction with alters tends to be frequent, as just shy of half of alters talk with egos almost daily (46.98%), 35.98% of alters interact with egos about weekly, and the remaining 17.07% talking to egos at least monthly.

Finally, looking at the alter co-membership characteristics, I find that most alters have either no co-membership ties (43.95%) or only one co-membership tie (44.95%). A remaining 11.10% of alters have two or more co-membership ties to

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[24] These analyses did not exclude alters based on age. Raw educational homophily may be stronger than estimated here. Specifically, some educational matching may be suppressed by not eliminating alters that may structurally not match their nominating ego (e.g., children).

voluntary associations. Around one-fifth of alters are people who egos met in a voluntary association (20.49%), highlighting the overlap that personal and associational spaces have as sources for social integration.

4.4.2 Bivariate Results

4.4.2.1 Bivariate Results: Homophily Characteristics

Table 4.5 presents the weighted group mean differences for the same-sex homophily measure. The additional categorical homophily measures (race, education, and religion) had no statistically significant group mean differences across any PAN influence measures. Therefore, I only report the group mean results for sex homophily here (see Appendix 4.A for the bivariate comparisons for all homophily variables).

Table 4.5 Weighted Group Mean Comparison between Alter Homophily Measures and Each Alter PAN Influence Measure

	Same Sex		
	Yes	No	t-value
Inf. Personal Network Density	47.48	50.77	2.46*
Inf. Co-membership Density	23.00	32.65	4.73***
Inf. PAN Density	38.73	46.75	6.54***
Inf. Prop. Co-member	23.27	32.18	4.43***
Inf. Prop. of VA with Co-members	11.09	21.44	4.75***
Inf. Fraction in Largest Component	20.96	27.20	6.38***
Inf. Fraction in Largest Bicomponent	23.20	30.11	4.81***
N	981	497	

Inf. = Influence
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When looking at sex-based homophily, gendered dynamics affect alter influence: across all PAN influence measures, alters whose sex matches their ego have a significantly lower level of influence on the PAN structure compared to different-sex alters. The initial findings, after pairing the nonsignificant differences for race, education, and religion homophily with the significantly lower average influence of same-sex alters, do not support Hypothesis 1: Alters that are homophilous on demographic attributes will have more influence for all PAN measures compared to dissimilar alters. Rather, counter to the expected relationship, homophily may not be a driving factor predicting an alter's influence on social integration within PANs.

However, when looking at the absolute difference in age, I find partial support for Hypothesis 1. Looking at Table 4.6, which presents the correlations between each influence measure and the age homophily measure, I find that the absolute difference in age is significantly negatively associated with influence for the majority of influence measures. These negative relationships suggest that as the difference in age between an ego and an alter increases, the expected influence that alter will have on the PAN measure decreases.

Table 4.6 Correlation between Network Influence Measures and Absolute Difference in Age between Ego and Alter

	Absolute Difference in Age (Ego-Alter)
Inf. Personal Network Density	-.018
Inf. Co-membership Density	-.196***
Inf. PAN Density	-.105***
Inf. Prop. Co-member	-.189***
Inf. Prop. of VA with Co-members	-.166***
Inf. Fraction in Largest Component	-.122***
Inf. Fraction in Largest Bicomponent	-.064
N dyads	1,478

Inf. = Influence
*** p < .001

For the personal network density and maximal PAN cohesion (fraction in the largest bicomponent) measures, however, the absolute difference in age is not significantly associated with influence on the PAN measures incorporating personal ties. This is an interesting result that illuminates important features for social integration. Age homophily has a strong influence on bridging personal and associational spaces, where shared memberships are more influential when alters are more similar in age. Age-based homophily for close personal ties, however, is not significantly associated with influence. This can be explained by the diverse set of individuals that make an ego's personal network, which often include kin and other alters that may vary widely in age. Overall, these bivariate results indicate partial support for Hypothesis 1, namely for age.

4.4.2.2 Bivariate Results: Tie Characteristics

Next, looking at the bivariate relationship between tie characteristics and alter PAN influence scores, Table 4.7 displays group means and pairwise mean comparison between the type of tie and alter influence, which tests Hypotheses 2-4. Across all alter PAN influence measures, spouses have the largest average influence—with a minimum average influence altering an ego's PAN structure by over a third (36.63%) to a higher average of nearly 60% structural change (58.66%). This finding provides support for Hypothesis 2: Alters who are spouses will be more influential across all PAN measures compared to other kin and non-kin alters.

The differences in influence between non-kin and other kin ties, however, are not consistent across all measures. Interestingly, non-kin alters have a higher average influence on co-membership-specific PAN measures, whereas other kin alters have a higher average influence on the personal network density measure that contains only personal ties. For example, non-kin alters have an average influence score of 25.82 on co-membership density compared to a score of 16.09 for other kin on the same measure (see Table 4.7). Supporting Hypotheses 3 and 4, these findings suggest that different types of alters are more influential to social integration depending on the context: personal ties are more kin-centric, whereas voluntary associations are not.

Table 4.7 Weighted Group Means and Pairwise Mean Differences between Tie Type and Each Alter PAN Influence Measure

	Means			**Pairwise Differences**		
	Non-Kin (NK)	Spouse (S)	Other Kin (OK)	NK-S	NK-OK	S-OK
Inf. Personal Network Density	46.02	57.66	48.93	-11.64*	-2.91*	8.73*
Inf. Co-membership Density	25.82	50.51	16.09	-24.69*	9.73*	34.42*
Inf. PAN Density	38.35	58.66	39.06	-20.31*	-.71	19.60*
Inf. Prop. Co-member	26.24	48.50	16.34	-22.26*	9.90*	32.16*
Inf. Prop. of VA with Co-members	11.67	40.44	7.97	-28.77*	3.70*	32.47*
Inf. Fraction in Largest Component	20.90	36.63	20.73	-15.73*	.17	15.90*
Inf. Fraction in Largest Bicomponent	22.84	40.30	23.57	-17.46*	-.73	16.73*
N	807	200	471			

Inf. = Influence
* Means are significantly at $p < 0.05$.

Assessing Hypothesis 5, Table 4.8 displays the group mean and pairwise mean comparison between the length of a relationship and each alter PAN influence measure. The length of a relationship is a significant predictor for personal network density, where the average influence is higher among longer-lasting relationships (5-10 years, 49.20; 10+ years, 50.19) compared to more recently developed relationships (<5 years, 44.34). Similarly, alters with the longest relationships more highly influence the overall cohesion of PANs, where relationships ten years or older have a higher average influence (23.71; 26.74) compared to newer relationships (21.22; 22.51). These differences support Hypothesis 5 and can be explained by the time it takes to develop close personal ties.

The length of the relationship, however, is not a significant indicator of influence for the co-membership-specific PAN measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members). This finding supports Hypothesis 6 and further highlights the differences that exist between the types of ties that bind egos to voluntary associations and those that bind egos to alters. Specifically, voluntary associations are more peripheral to the social environment of individuals than their core personal networks are, and shared memberships are not contingent on the length of the relationship, as they do not require the same length of time to develop.

Table 4.8 Weighted Group Means and Pairwise Mean Differences between Length of Relationship and Each Alter PAN Influence Measure

	Means			Pairwise Differences		
	< 5 yrs.	5-10 yrs.	10+ yrs.	<5-5-10	>5-10+	5-10-10+
Inf. Personal Network Density	44.34	49.20	50.19	-4.86*	-5.85*	-.99
Inf. Co-membership Density	26.61	28.35	25.85	-1.74	.76	2.50
Inf. PAN Density	38.06	42.39	42.73	-4.33*	-4.67*	-.34
Inf. Prop. Co-member	26.62	28.40	25.85	-1.78	.77	2.55
Inf. Prop. of VA with Co-members	11.37	14.50	16.10	-3.13	-4.73	-1.60
Inf. Fraction in Largest Component	21.22	24.02	23.71	-2.80	-2.49*	.31
Inf. Fraction in Largest Bicomponent	22.51	26.13	26.74	-3.62	-4.23*	-.61
N	318	221	939			

Inf. = Influence
* Means are significant at $p < 0.05$.

Unlike the length of the relationship, the frequency of interaction between an ego and alter has a more uniform effect: alters that interact with egos more frequently have, on average, a significantly higher influence across all alter PAN influence measures (see Table 4.9). In fact, the magnitude of difference between monthly interactions and daily interactions is higher for the co-membership-specific measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members) compared to the PAN measures that incorporate both personal and associational ties. For example, alters with monthly interactions have a 6.89% difference in the proportion co-member, whereas daily interactions with an alter has a 33.35% difference on the proportion co-member measure. These findings support Hypothesis 6 and can be explained by the role that frequent interactions have in structuring a PAN's connectivity, regardless of whether those connections are personal or associational.

Table 4.9 Weighted Group Means and Pairwise Mean Differences between Interaction Frequency and Each Alter PAN Influence Measure

	Means			**Pairwise Differences**		
	Monthly (M)	Weekly (W)	Daily (D)	M-W	M-D	W-D
Inf. Personal Network Density	42.05	47.32	52.02	-5.27*	-9.97*	-4.70*
Inf. Co-membership Density	17.17	21.22	33.69	-4.05	-16.52*	-12.47*
Inf. PAN Density	34.29	38.37	46.62	-4.08*	-12.33*	-8.25*
Inf. Prop. Co-member	17.57	21.63	33.25	-4.06	-15.68*	-11.62*
Inf. Prop. of VA with Co-members	6.89	9.02	21.93	-2.13	-15.04*	-12.91*
Inf. Fraction in Largest Component	18.98	20.59	26.62	-1.61*	-7.64*	-6.03*
Inf. Fraction in Largest Bicomponent	19.09	23.42	29.69	-4.33*	-10.60*	-6.27*
N	274	532	672			

Inf. = Influence
* Means are significant at $p < 0.05$.

4.4.2.3 Bivariate Results: Co-membership Characteristics

Two additional variables are used to explore Hypotheses 7 and 8: an indicator for having met the alter at an association and the number of co-membership ties. Table 4.10 displays the weighted mean differences between alters who met the ego in an association to those that did not. Two of the alter PAN influence measures are significant: co-membership density and proportion co-member. Alters that ego met in an association have a higher average influence on integrating the personal and the associational, acting as bridges within PANs. Personal ties formed within an associational context, while not definitionally structuring the PAN measures, still play a key role in bridging personal and associational contexts. This finding highlights the need to explore the contextual features of ties rather than only the absence or presence of a specific type of tie.

Table 4.10 Weighted Group Mean Comparison between Meeting at an Association and Each Alter PAN Influence Measure

	Yes	No	t-value
Inf. Personal Network Density	48.66	48.63	.31
Inf. Co-membership Density	34.29	24.35	-4.58***
Inf. PAN Density	42.07	41.41	-.49
Inf. Prop. Co-member	34.71	24.26	-4.84***
Inf. Prop. of VA with Co-members	12.60	15.27	1.11
Inf. Fraction in Largest Component	22.66	23.27	.55
Inf. Fraction in Largest Bicomponent	25.17	25.74	.38
N	301	1,177	

Inf. = Influence
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.11 displays the weighted group means and pairwise mean differences across the number of co-membership ties alters have. As a note, no bivariate, alter-level, mean comparisons are made for co-membership-specific measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members), as these measures are composed only of alter-association ties. Thus, definitionally, an alter with any level of co-membership ties would influence the co-membership-specific PAN measure. Yet, I still find support for Hypothesis 8, where higher levels of co-membership ties are associated with increased personal connections. For example, compared to alters with no co-membership ties, alters with one co-membership tie (50.37) or two or more co-membership ties (51.85) have higher average influence on personal network density. Furthermore, alters with more co-membership ties are likely more highly integrated into the broader PAN, and therefore are more influential in the connectivity of the network as a whole. This supports the overall claim of this dissertation: social integration is a nuanced phenomenon that binds individuals across multiple types of ties that often overlap.

Table 4.11 Weighted Group Means and Pairwise Mean Comparison between the Number of Co-membership Ties and Each Alter PAN Influence Measure

	Means			Pairwise Differences		
	0	1	2+	0-1	0-2+	1-2+
Inf. Personal Network Density	46.04	50.37	51.85	-4.33*	-5.81*	-1.48
Inf. Co-membership Density	-	-	-	-	-	-
Inf. PAN Density	33.38	47.41	50.15	-14.03*	-16.77*	-2.74
Inf. Prop. Co-member	-	-	-	-	-	-
Inf. Prop. of VA with Co-members	-	-	-	-	-	-
Inf. Fraction in Largest Component	18.23	26.39	29.49	-8.16*	-11.26*	-3.10
Inf. Fraction in Largest Bicomponent	18.16	29.82	38.18	-11.66*	-20.02*	-8.36*
N	671	654	135			

Inf. = Influence
* Means are significant at $p < 0.05$.

4.4.3 Multivariate Results

Extending the bivariate results, I use multivariate regression models to explore how homophily, tie type and strength, and co-membership characteristics together are associated with an alter's influence on the PAN measures. For all seven alter influence measures, I present two models: (1) Model 1 predicts alter influence as a function of homophily, the tie type and strength characteristics, and the co-membership characteristic "met at an association" (testing Hypotheses 1-7), and (2) Model 2 incorporates the co-membership characteristic of the number of co-membership ties as a covariate (Hypothesis 8).

4.4.3.1 Multivariate Results: Model 1—Homophily Characteristics

Table 4.11 shows Model 1 for all seven alter influence measures. Compared to the bivariate results, age is the only significant homophily predictor after controlling for alter characteristics and tie characteristics.[25] The partial support for Hypothesis 1 is based on the age homophily of alters, specifically for the co-membership PAN measures: as the difference in age between an ego and their alter increases, the alter's expected influence decreases. In the multivariate models, age homophily is significant for all alter influence measures, aside from personal network density, after controlling for alter-level characteristics. A lack of age homophily influencing personal network density can be explained by the diversity of personal networks, where personal ties often include a high proportion of kin and need not be age-based.

The co-membership-specific PAN measures (co-membership density, proportion co-member, and proportion of voluntary associations with co-members), however, are contingent on age similarity. For example, with every one-year difference in age between an ego and an alter, the alter's influence on co-membership density is expected to decrease by 0.225 percentage points. For the co-membership-specific PAN measures (isolated to alter-association ties), these significant homophilous age effects highlight important nuances about how alters influence social integration. Alters that are a similar age are associated with greater influence on the connectivity of personal and associational ties, indicating that voluntary associations may be targeting similarly aged individuals.

[25] Same sex is significantly negatively associated with an alter's PAN influence in the bivariate tests and in models incorporating only homophily tie characteristics. Once incorporating other tie characteristics (i.e., tie type), however, these associations are no longer significant. See Appendix 4.B for the model limited to homophily and alter characteristics.

4.4.3.2 Multivariate Results: Model 1—Tie Characteristics

Next, I transition to the types of tie characteristics associated with an alter's influence: tie type and tie strength (see Table 4.12). Compared to non-kin, spouses have significantly higher influence across all PAN measures, supporting Hypothesis 2. Spouses' range of expected influence is rather large, topping off at over 20% for the influence on the proportion of voluntary associations with co-members (20.55). The overwhelming influence of spouses highlights the saliency of close ties and their ability to structure social environments, even beyond personal ties.

Spouses are often an ego's closest interpersonal relationship and have the largest expected influence across all PAN measures. This suggests that there is high overlap in the personal and associational ties of couples and that spousal ties are important in an ego's personal and associational integration. Although previous research has identified the role that spouses have in structuring personal networks (see Cornwell 2012, for example), that research has not extended to associational ties, let alone the combination of personal and associational ties.

When comparing the influence that other types of alters have on social integration, I find no significant differences between non-kin and other kin alters for the PAN measures isolated to personal ties (personal network density) or the measures that combine personal and associational ties (PAN density, fraction in the largest component, and fraction in the largest bicomponent). Therefore, I find no support for Hypothesis 3: After spouses, other kin alters will have more influence on the PAN measures that are isolated to personal ties (personal network density) compared to non-kin alters.

Table 4.12 Model 1. Seven Weighted Multilevel and Clustered OLS Regression Models, Homophily, Tie, and Co-membership Characteristics Predicting Alter Influence[1,2]

	Inf. Personal Net. Density[a]	Inf. Co-mem. Density[b]	Inf. PAN Density[a]	Inf. Prop. Co-member[b]	Inf. Prop. VA w/ Co-memb.[b]	Inf. Frac. in Largest Comp.[a]	Inf. Frac. in Largest Bicomp.[a]
Homophily Characteristics							
Same Sex	-.113	-.540	-.935	-.829	-.149	-.280	-1.138
Same Race	1.459	-2.045	-1.250	-2.628	-2.599	-3.191	-.780
Same Education	.155	.187	-.876	.286	1.877	.043	-.495
Same Religion	1.581	.172	1.247	-.221	.837	.011	2.107
Abs. Difference Age	-.025	-0.225*	-0.117*	-0.211*	-0.229*	-.043	-.082
Tie Characteristics							
Tie Type							
Role Relation							
Spouse	7.356***	17.10***	12.85***	14.53***	20.55***	11.56***	11.23***
Other Kin	1.857	-7.870**	-.297	-8.338**	-5.195	-.619	-.219
Tie Strength							
Length of Relationship							
5-10 yrs.	6.514**	-.040	2.785	.511	-.367	1.889	2.279
10+ yrs.	6.967***	5.207	5.285***	5.785*	6.034*	3.073*	4.334*
Interaction Frequency							
Weekly	4.242**	6.055**	4.842***	6.111**	3.235	2.288*	4.426**
Daily	6.420***	13.90***	8.643***	13.79***	8.771**	4.537***	7.284***
Co-membership Characteristics							
Met at Association	4.297*	12.82***	5.198***	13.02***	1.396	2.702*	4.093*
Control Variables							
Sex (female)	1.651	2.686	1.512	2.724	4.750**	1.143	1.670
Race (non-white)	.346	1.909	1.917	1.203	1.189	.440	3.564
Education							
BA	-1.010	-.213	-.084	-.452	.460	.422	-.009
HT BA	-.583	1.155	.674	.695	2.661	1.308	.123
Religion							
Protestant	-3.551	1.404	-.300	1.301	.864	-.115	.660
Catholic	-2.833	.791	-.633	.621	.784	-.225	-.014
other	-1.500	.080	1.443	.204	.385	.133	4.450
Age	-.012	-.070	-.039	-.066	-.079	-.035	-.039
PAN Degree (centered)	-2.075**	-2.440***	-3.463***	-2.442***	-2.306***	-2.248***	-2.351***
Intercept	37.82***	17.09**	33.29***	18.09**	7.886	20.76***	16.94**
σ^2(ego)	334.3***	—	25.87*	—	—	27.75**	62.660
σ^2(Intercept)	239.1***	—	203.5***	—	—	123.3***	325.3***

[1] Estimates are weighted, and standard errors are adjusted for clustering and stratification.
[2] Analytic sample is comprised of 1,478 alters nested in 393 egos.
[a] Multilevel Generalized Regression Models
[b] Clustered OLS Regression Models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

However, I find that non-kin alters hold more influence for the PAN measures that capture the integration of personal and associational contexts, supporting Hypothesis 4 (see Model 1; Table 4.12). Specifically, for the co-membership-specific measures (co-membership density and proportion co-member), other kin have an expected lower level of influence than non-kin alters. For co-membership density and proportion co-member particularly, the expected level of influence is 7.870 and 8.338% lower, respectively. These findings highlight the role that voluntary associations play in integrating weaker and potentially more diverse ties. Many types of voluntary associations, such as sports clubs or Greek organizations, are not kin-centric but instead provide a space to form new ties or participate in activities with friends or other non-kin alters.

When analyzing the characteristics of tie strength (Hypotheses 5 and 6), I find that both the length of a relationship and the frequency of interaction that alters have with an ego have a consistent and strong association with an alter's influence. The longest established and most frequently activated alter ties (10+ years and daily) have the highest expected influence across all PAN measures (see Table 4.12). For alters that an ego has been tied to for 10 or more years, the only non-significant association is co-membership density (5.207). These findings are, in part, counter to the expected association between the length of a relationship and the co-membership-specific PAN measures (Hypothesis 5).

Although associational ties may be hypothesized as more transient, in the PAN context which accounts for the dependency between personal and associational ties, core network members are stronger relationships, and therefore, have an influence over more than just personal ties. Additionally, there is support for Hypothesis 6. I find that the length of relationship is associated with each PAN measure: more frequent interactions are associated with higher influence, regardless of whether the tie is personal or associational.

4.4.3.3 Multivariate Results: Model 1—Co-membership Characteristic (Met at Association)

Finally, focusing on Hypothesis 7, I examine the contextual role of tie formation. Still looking at the first model (Table 4.12), I find that meeting an alter in an association is positively associated with an alter's influence, except for the measure of the proportion of voluntary association with co-members. Having met an alter in an association is related to a higher level of influence (2.70% to 13.02%) on personal and paired personal and associational measures. Overall, this suggests that associational and personal ties bleed together, and meeting in an association creates stronger network ties and greater PAN integration.

4.4.4 Multivariate Results: Model 2—Differences in Alter Characteristics when Accounting for Co-membership Ties.

The second empirical model includes co-membership ties as a covariate. Here, the goal is to identify which alter characteristics are still significant predictors of PAN influence, net of co-membership ties. Controlling for alter-level influence can account for the variability of co-membership ties between alters and can pinpoint which alter characteristics are most salient, net of alter-association ties.

4.4.4.1 Multivariate Results: Model 2—Co-membership Ties

Table 4.13 displays Model 2, which predicts an alter's influence after controlling for all covariates in the first model, then adding the number of co-membership ties an alter has as a covariate. Focusing specifically on the number of co-membership ties, alters with at least one co-membership tie, compared to alters with no co-membership ties (that is, no shared memberships in any of the ego's voluntary associations) are significantly associated with a higher influence on the majority of PAN measures. This is partially definitional, but not for every PAN measure.

The co-membership ties of alters do not uniformly influence the PAN measures incorporating either only personal ties (alter-alter) or personal and associational ties (alter-alter and alter-association). Rather, the average influence of alters with co-membership ties varies in its magnitude across the measures. For example, net of other alter characteristics, co-membership ties are non-influential on personal network density (the single PAN measure in these analyses that incorporates only personal ties). Contrary to the bivariate results, once controlling for other alter characteristics—namely spouses, long-lasting relationships, and frequent interactions—there is no longer a significant difference in an alter's influence based on their co-membership ties; thus, this finding does not support Hypothesis 8. This indicates, particularly for personal connections, that other characteristics of alters are stronger predictors of social integration than co-membership ties.

When accounting for a wider set of network ties, however, alters with co-membership ties have more influence on the cohesiveness of the wider PAN beyond personal ties. Particularly for the minimal (fraction in the largest component) and maximal (fraction in the largest bicomponent) cohesion measures, the larger the number of co-membership ties, the greater the level of integration, which partially supports Hypothesis 8. Overall, these findings confirm that different tie characteristics are contingent on the context and scope of a network, where tie characteristics specific to alters may be activated differently in personal contexts than in associational contexts.

4.4.4.2 Multivariate Results: Model 2—Differences in Alter Characteristics from Model 1

When including co-membership ties within the model, I identify three results that contrast with those from Model 1 (which does not account for the number of co-membership ties). First, in Model 2, age homophily is only significant for co-membership-specific measure (co-membership density, proportion co-member, and proportion of voluntary associations with co-members) (see Table 4.13). This partially confirms Hypothesis 1: within measures that are specific to alter-association ties, age is a major integrating factor, as associations are highly age specific. While only significant for the co-membership-specific measures, this finding confirms which types of alter ties are influential in linking personal and associational networks: more similarly aged alters have an expected higher influence on co-membership integration.

Table 4.13 Model 2. Seven Weighted Multilevel and Clustered OLS Regression Models, Homophily, Tie, and Co-membership Characteristics Predicting Alter Influence[1,2]

	Inf. Personal Net. Density[a]	Inf. Co-mem. Density[b]	Inf. PAN Density[a]	Inf. Prop. Co-member[b]	Inf. Prop. VA w/ Co-memb.[b]	Inf. Frac. in Largest Comp.[a]	Inf. Frac. in Largest Bicomp.[a]
Homophily Characteristics							
Same Sex	-.193	-1.551	-1.253	-1.563	-.767	-.550	-1.711
Same Race	1.191	-2.034	-2.732	-1.687	-2.820	-4.705	-1.709
Same Education	.235	.845	-.288	.956	2.233	.526	-.296
Same Religion	1.541	.738	1.893	.633	1.076	.276	2.150
Abs. Difference Age	-.022	-.190**	-.057	-.191**	-.206*	-.013	-.056
Tie Characteristics							
Tie Type							
Role Relation							
Spouse	6.770***	9.315**	7.978***	8.116*	15.98***	8.404***	7.020**
Other Kin	2.130	-.353	2.045	-.559	-1.167	.972	2.184
Tie Strength							
Length of Relationship							
5-10 yrs.	6.442**	-1.971	3.301*	-1.986	-1.281	2.235	2.002
10+ yrs.	6.800***	1.106	4.304**	1.229	3.913	2.593*	3.108
Interaction Frequency							
Weekly	4.005*	1.470	2.793*	1.647	.710	1.250	2.384
Daily	5.923**	4.125	4.622**	4.099	3.431	2.240*	3.736*
Co-membership Characteristics							
Met at Association	3.574	-7.191**	.649	-7.512**	-9.372**	-.390	-.911
Co-membership Ties							
1	1.664	43.47***	15.98***	45.51***	23.17***	10.01***	13.17***
2+	3.836	49.10***	25.68***	41.94***	28.47***	17.28***	23.03***
Control Variables							
Sex (female)	1.687	3.997**	1.813*	4.128**	5.442**	1.311*	2.058
Race (non-white)	.015	-.573	-.906	-.190	-.427	-1.691	1.316
Education							
BA	-1.003	.675	-.053	.411	.949	.219	.160
HT BA	-.573	1.685	.689	1.143	2.970	1.377	.015
Religion							
Protestant	-3.617	-.103	-1.359	-.279	.062	-.599	.237
Catholic	-2.818	2.611	-1.288	2.663	1.721	-.289	-.008
other	-1.471	.094	1.220	.147	.410	.152	4.280
Age	-.006	-.006	-.032	.004	-.046	-.022	-.025
PAN Degree (centered)	-2.141**	-2.829***	-4.218***	-2.523***	-2.592***	-2.639***	-2.896***
Intercept	37.23***	.402	29.28***	-.195	-.808	17.79***	13.43**
σ^2(ego)	332.2***	—	102.8***	—	—	62.27***	103.4***
σ^2(Intercept)	238.5***	—	111.3***	—	—	84.10***	256.3***

[1] Estimates are weighted, and standard errors are adjusted for clustering and stratification.
[2] Analytic sample is comprised of 1,478 alters nested in 393 egos.
[a] Multilevel Generalized Regression Models
[b] Clustered OLS Regression Models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second, there are fewer length-of-relationship measures associated with an alter's influence. Once accounting for the number of co-membership ties a given alter has, the co-membership-specific PAN measures are not significantly associated with an alter's influence. This finding partially confirms Hypothesis 5: Alters that have been tied to egos for a longer time will have more influence on all PAN measures, compared to newly developed ties, but the difference between the two groups will be smaller for co-membership-specific measures. While the length of a relationship is more influential for personal network ties, an alter's influence on the alter-association measures are not significantly associated with relationship length. For frequency of interaction however, the type of tie (personal or associational) is not associated with specific tie characteristic activation. Rather, high levels of contact are expected to have higher levels of influence across the board.[26]

Finally, and most strikingly, I find that once controlling for the number of co-membership ties, meeting at an association is no longer a significant predictor of integration for the personal network and paired personal and associational network measures (see Model 2, Table 4.13). And, for the co-membership-specific measures, there is a reversal in the direction of the expected influence, where alters that an ego met in an association are significantly negatively associated with alter influence. Therefore, contrary to the findings from Model 1, I find no support for Hypothesis 7.

Alters who bridge associations are significantly more influential if their tie with the ego was not formed in the organization. Net of the number of co-membership

[26] These findings may in part be driven by the network generator used for nominating alters, specifically discussion partners. There may be bias in the network generator where individuals nominate alters with whom they are frequently in contact. Other research should explore a PAN structure and alter influence using other egocentric name generators.

ties, alters that an ego met at an association have an expected lower level of influence on integrating personal and associational ties in a PAN than ties not formed in an association. This may be because ties to alters that formed in associations are "weak" and not highly connected to other persons or associations within the PAN. Put differently, alters that an ego met at an association are more peripheral to the PAN—they are integrated into fewer associations, and, once controlling for the number of co-membership ties they have, they are less interpersonally connected to other alters.

Take, for instance, an alter that an ego met in a sports club. If this ego also shares memberships, such as church, with other alters, losing ties with the alter who is isolated to the sports club will not influence the overall co-membership density. Rather, the other alters are likely stronger, and their co-membership ties may be more concentrated. This is a major finding that further illuminates the complexity of social ties in integrating social life. Contextual features, such as where a tie was formed, influence the bridging capacity of alters to other social contexts, such as voluntary associations. Taken together, the co-membership characteristics of alters play a complex role in the influence alters have on an individual's social integration. Overall, these results highlight a commonly identified theme from previous research: tie characteristics are more nuanced than just a connection between two individuals.

4.5 DISCUSSION

This chapter set out to explore the role that personal ties have in integrating an individual's personal affiliation network (PAN). While previous research has often and consistently identified compositional features of ego networks as important in shaping the structure of the network, previous research has failed to explore how alters more broadly influence individual social integration. Using a PAN structure incorporating an ego's personal and associational ties concurrently, I identify which homophily, tie type and strength, and co-membership characteristics of alters are most influential in integrating PANs. Using a subset of egos from the 2006 NVAS who share voluntary association memberships with their alters (i.e., co-membership ties), I explore differences in alter characteristics for 1,478 alters nominated by 393 egos. Relying on univariate, bivariate, and multivariate statistics, I test eight hypotheses. Table 4.14 provides a summary of the findings, specific to each hypothesis.

When assessing the role of alters in individual social integration in PANs, I identified four major findings: (1) similarly aged alters are most influential in bridging personal and associational ties, (2) spouses are integral to individual social integration, (3) strong ties that are long lasting and frequently activated are highly influential, and (4) the extent to which ties with alters influence social integration depends on the context in which ties are formed.

In the case of the first major finding, while I identify a significant homophily effect for age for the co-membership-specific PAN measures, the other homophily measures do not predict an alter's influence on an individual's integration. In fact, I find that sex homophily operates in the opposite direction: same-sex alters have an expected lower level of influence across all PAN measures in the bivariate analyses. Additionally, in both of the multivariate models, age homophily is the only significant homophily measure associated with an alter's influence. Therefore, I identify only partial support for Hypothesis 1 isolated to age.

Table 4.14 Summary Table of Hypotheses for Homophily, Tie, and Co-membership Characteristics Associated with Alter Influence on PAN Structure

<table>
<tr><th>#</th><th colspan="5">Hypothesis</th><th colspan="3">Support</th></tr>
<tr><th></th><th colspan="5"></th><th>BV</th><th>M1</th><th>M2</th></tr>
<tr><td></td><td colspan="5">Homophily Characteristics</td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">1</td><td colspan="5">Alters that are homophilous on demographic attributes will have more influence for all PAN measures compared to dissimilar alters.</td><td rowspan="3">+</td><td rowspan="3">+</td><td rowspan="3">+</td></tr>
<tr><td>Sex</td><td>Race</td><td>Education</td><td>Religion</td><td>Age</td></tr>
<tr><td>+</td><td>×</td><td>×</td><td>×</td><td>✓</td></tr>
<tr><td></td><td colspan="5">Tie Characteristics</td><td></td><td></td><td></td></tr>
<tr><td></td><td colspan="5">Tie Type</td><td></td><td></td><td></td></tr>
<tr><td>2</td><td colspan="5">Alters who are spouses will be more influential across all PAN measures compared to other kin and non-kin alters.</td><td>✓</td><td>✓</td><td>✓</td></tr>
<tr><td>3</td><td colspan="5">After spouses, other kin alters will have more influence on the PAN measures that are isolated to personal ties compared to non-kin alters.</td><td>✓</td><td>×</td><td>×</td></tr>
<tr><td>4</td><td colspan="5">Non-kin alters will have more influence on the co-membership-specific PAN measures compared to other kin alters.</td><td>✓</td><td>+</td><td>×</td></tr>
<tr><td></td><td colspan="5">Tie Strength</td><td></td><td></td><td></td></tr>
<tr><td>5</td><td colspan="5">Alters that have been tied to egos for a longer time will have more influence on all PAN measures, but less for co-membership specific measures, compared to more newly developed ties.</td><td>✓</td><td>✓</td><td>+</td></tr>
<tr><td>6</td><td colspan="5">Alters that more frequently interact with an ego will have more influence on all PAN measures compared to alters where interaction is less frequent.</td><td>✓</td><td>✓</td><td>+</td></tr>
<tr><td></td><td colspan="5">Co-membership Characteristics</td><td></td><td></td><td></td></tr>
<tr><td>7</td><td colspan="5">Alters that an ego met in a voluntary association will have more influence on the co-membership-specific PAN measures compared to alters that the ego did not meet in an association.</td><td>+</td><td>✓</td><td>×</td></tr>
<tr><td>8</td><td colspan="5">Alters with co-membership ties will have more influence on PAN measures isolated to personal ties or combined personal and associational ties than alters with no co-membership ties.</td><td>✓</td><td>N/A</td><td>+</td></tr>
</table>

BV = bivariate results; M1 = Model 1 results; M2 = Model 2 results
✓ Supported; + Partial Support; × Not Supported

There are two important points to consider when interpreting these results. First, alters that are most influential share association memberships with egos to organizations that are age specific. This is an important detail that can inform what types of organizations can provide support to their members. Additionally, for researchers studying the associative habits and social networks of individuals, knowing how influential similarly aged alters are for bridging personal and associational ties can pinpoint key alters for increased civic engagement and support.

Second, although the hypothesized results for homophily are generally not supported (aside from age), there may be an alternative explanation. While homophily has an established influence on individual behaviors and has been proven to be strong in personal networks, it may be operating as an equalizer of alters within PANs. Alters that are highly homophilous, for example, likely share many of the same attributes as their ego. These homophilous features may also extend to other aspects of the network, such as personal and associational ties. Therefore, the overall influence of a given alter within a highly homophilous network may also be homophilous, where an alter's influence is similar across all alters in the PAN. Therefore, the lack of education, race, and religion homophily influencing PAN measures may be explained by alters being so similar (matching on many or all characteristics) that their overall influence washes out. Using influence as operationalized in this chapter as an example, if homophily is operating in this counter fashion, then removing the ties of one alter would be no more influential on the PAN measure than removing another alter.

The second major finding of this chapter is specific to alter role types and their differential influence on individual social integration. Overall, I find support for Hypothesis 2 and 4, and partial support for Hypothesis 3. Overwhelmingly, spouses have the highest level of influence on social integration net of all other alter characteristics. While non-kin alters have higher levels of influence on the co-membership-specific PAN measures (those that bridge personal and associational ties), I do not find that other kin are as influential to personal networks as anticipated. Rather, in the PAN context, other kin alters are no more influential than non-kin to the density or cohesion of PANs.

These findings highlight the salient role that spouses have in integrating their partner's social life and illustrate the complexities of social connectivity using more precise measures of social integration. Regardless of the type of tie (alter-alter or alter-association), spouses dramatically influence how much personal and associational social contexts overlap, how connected personal networks are, and how cohesive the PAN is. Losing a spousal tie, for example, may shatter a person's network, reducing not only their personal integration but their associational integration as well.

Exploring tie characteristics specific to the strength of the tie, I find that longer maintained relationships and more frequently activated ties are associated with higher levels of influence; however, their effect depends on the source of the connection. For PAN measures specific to personal ties (personal network density), I find that alters who have been tied to an ego for a longer time are expected to be more influential, net of all other tie characteristics. However, for the maximal cohesion measure (fraction in the largest bicomponent), the length of the relationship is not associated with an alter's influence, although it is significant for the less stringent measures of connectivity (PAN density, fraction in the largest component). These findings, therefore, partially support Hypothesis 5. Importantly for social integration, these findings emphasize the way that strong and lasting ties make personal networks more durable.

The length of a relationship, however, is not a significant predictor of co-membership-specific PAN measures in either model. Thus, alters bridging alters and associations need not be as durable. Supporting Hypothesis 6, this finding highlights the shorter lifespan of voluntary association memberships compared to personal ties; shared memberships, which operate as weak ties, can be established for less time. Frequency of interaction is also an important indicator predict alter influence. In partial support of Hypothesis 7, I find that interactions between alters and egos activates those ties, so more frequent interaction increases the influence that an alter has.

Taken together, my findings about tie characteristics align with previous research: social ties are not just about the quantity of ties but with their quality. Interestingly, however, the *quality* of ties may be operationalized differently depending on the context. For personal ties, durability and frequent activation strengthen their influence. On the other hand, having well-established, durable ties is not needed for co-membership ties bridging individuals and associations. Rather, the ability of ties to integrate personal and associational contexts is more influenced by frequent interaction.

In the fourth main finding of this chapter, I find that co-membership characteristics are important for predicting alter influences. When focusing on the contextual features of tie formation, I find that meeting alters in an association has a unique influence on an ego's social integration. Within the first model (Model 1), which does not account for the number of co-membership ties an alter has, I find partial support for Hypothesis 7, where meeting an alter in an association has a significant positive association on the co-membership-specific measures.

Additionally, net of other homophily and tie characteristics, I find that alters who met the ego within an association also influence the personal and paired personal and associational PAN measures. This suggests that these alters integrate the personal and associational aspects of a PAN.

Alternatively, when controlling for the number of co-membership ties, there is a reversal in the influence of meeting an alter in an association, specifically for the co-membership-specific measures (Model 2), where I find that ties to alters that are formed in associations are expected to be less influential compared to alters that an ego met in another context. While I have identified that voluntary associations indeed operate as an integrating space within the immediate social environments of individuals, not all ties provide the same integrating effects.

While the number of co-membership ties alters have is important for conceptualizing PANs and their relationship to social integration, I only find partial support for Hypothesis 8 after controlling for other tie characteristics. When focusing on personal network density—the only measure in these analyses that is limited to personal (alter-alter) ties—I find that the number of co-memberships of an alter has no effect on the extent to which that alter influences personal network integration. This is particularly important for contextualizing the interplay of personal and associational ties within social environments.

4.6 CONCLUSION

Alter characteristics have commonly been used to identify key compositional features of ego networks which have been used to predict structural features of networks (Agneessens et al. 2006; Fiorillo and Sabatini 2011; McPherson et al.

2001; Smith et al. 2014). Existing studies on the composition of ego networks have two main shortcomings: (1) these studies are limited to personal ties and (2) they do not assess how alter characteristics influence social integration. Therefore, within the context of PANs, it is particularly important to identify the influence that alters have on integrating an ego's network by incorporating personal and associational ties. While the study in the previous chapter explored the ego demographic correlates of the PAN measures, it was not able to either identify *which* core members bridge personal and associational environments, nor could it identify salient alter-level characteristics that foster social integration. Therefore, this chapter aimed to (1) establish the relative influence that actors in a network have on the social integration of individuals and (2) test whether specific alter characteristics are associated with individual-level social integration. These aims provide insight into who influences social integration but also how their influence differs across more nuanced social integration measures. This study, therefore, adds needed detail to current ego network research focused on compositional and structural features.

The specific analyses in this chapter are dyadic, using a subsample of egos who share any association memberships with their alters (n = 393), allowing me to assess differences in alter influence for a total of 1,478 alters. Looking a seven PAN measures, this study identifies the influence of spouses, alters with whom an ego has a long-lasting and deep relationship, and age-homophilous alters. Additionally, where a tie was formed (that is, whether a tie was formed in an association or not) influences co-membership-specific PAN measures. I identified that while meeting an alter in an association is integrating, creating a stronger tie to the specific organization, the tie is also isolated to that associational context and does not extend the density or cohesion of the larger PAN. These results have larger implications for researchers interested in understanding outcomes of social support, civic engagement, and well-being more generally.

Identifying known influential alters can be particularly useful for interventions in times of need. For example, knowing the significant influence of spousal ties can aid practitioners in reducing the shock that a divorce may have on an individual. Additionally, having a better understanding of the influence of specific tie characteristics, and identifying the contexts on which these characteristics depend, can inform the generation of ties to supplement an individual's social integration. Overall, this study builds on the previous studies in this dissertation to better understand not only how social integration can span across multiple types of ties, but also how other relational dynamics are associated with social integration—namely, how influential close personal ties are.

CHAPTER 5 CONCLUSION

Over time, society has increased in complexity, transforming how, and in what ways, individuals are relationally connected. Many of these changes have challenged assumptions about social integration. Social ties have become more diverse and now overlap in nuanced ways that traditional measures of social integration cannot fully capture. In response to the current context of social relationships, this dissertation has three main goals: (1) to develop a methodological framework to measure social integration within ego networks more precisely; (2) to reexamine established relationships between social integration and ego demographic correlates when using more precise measures of social integration; and (3) to identify which close personal ties influence social integration and to what extent they do so. In this final chapter, I discuss how this dissertation fulfilled these goals, describe some outstanding methodological limitations, and identify ways this framework could be applied to the study of social integration more broadly.

5.1 GOAL 1: MORE PRECISELY MEASURE SOCIAL INTEGRATION WITHIN EGO NETWORKS

The second chapter of this dissertation develops a methodological basis for measuring social integration within ego networks. I began the chapter by detailing how current social integration research on ego networks and voluntary associations tends to view each separately, and then I justify why combining personal and associational ties is fruitful. I develop a framework I call the personal affiliation network (PAN), a modified ego network data structure incorporating multiple types of ties. Using the PAN data structure, I develop a series of measures that account for personal and associational ties concurrently.

With the larger goal of developing more precise integration measures, Chapter 2 establishes a network structure that captures personal and associational ties simultaneously (Aim 1) and constructs a series of measures that more precisely capture social integration using the PAN data structure (Aim 2). The entire dissertation builds on this framework. The two empirical studies that come after the second chapter take the PAN framework and apply it to a nationally representative sample of US adults. Each study in this dissertation extends current ego network methods to explore how PAN measures better capture features of individual social integration.

5.2 GOAL 2: IDENTIFY WHO IS SOCIALLY INTEGRATED WITHIN A PAN CONTEXT

The second goal of this dissertation is to apply the PAN framework to actual data, reexamining known relationships between social integration and ego demographic correlates. Using the National Voluntary Association Study (NVAS) as a case study, Chapter 3 applied the PAN framework to (1) describe the distribution of, and the relationship between, measures of social integration using personal and associational ties (Aim 3) and (2) establish whether individual sociodemographic characteristics are associated with the PAN measures (Aim 4).

This second study, which conducts two sets of analyses, explores how the PAN measures are distributed as well as the relationship between the measures when applied to the NVAS data. The results indicate that (1) a high level of overlap exists between personal and associational contexts, (2) there are nuanced patterns in the structure and composition of PAN that are not uniform across each measure, (3) personal and associational ties may supplement each other within PANs, and (4) there are structural differences in social integration between individuals whose alters are members of the same voluntary associations as them and those whose alters are not co-members of the same groups. These findings extend previous research identifying important nuances in social integration across individuals: personal and associational ties coexist in individuals' social lives, overlapping, supplementing each other, and integrating their social environment. Substantively, a researcher could use the PAN measures to differentiate social integration across different contexts and identify the conditions under which social integration is amplified or dampened. Additionally, future studies could identify which, and to what extent, associational ties can offset personal ties, potentially supplementing individual social integration.

The second set of analyses takes up the questions of *who* is integrated and *how* a PAN structure challenges current findings. Exploring these questions using ego demographic correlates to predict each PAN measure, I find that (1) demographic variation in social integration does not fully align with previous findings, and (2) social integration measures specific to co-membership ties (alter-association ties) are not differentiated across ego demographic groups. These findings suggest that although personal networks and voluntary associations may integrate egos to different levels of society, their integrating capacities supplement each other: associational ties may supplement personal ties, and vice versa. Additionally, these findings reinforce the importance of a PAN framework as social integration extends beyond personal ties alone. Overall, differentiating these complex contextual features within ego networks would open up new avenues for research and sharpen the focus of current findings.

5.3 GOAL 3: IDENTIFY WHO INTEGRATES AN EGO'S PAN

The third goal of this dissertation is to identify which of those people who are closest to an individual influence their social integration and to what extent they do so. Still using the NVAS data, Chapter 4 extends the previous study by shifting from the characteristics of individuals (egos) to the social ties (i.e., alters) that bind their PANs. To fulfill this larger goal, this study aimed to establish the relative influence that actors in a network have on the social integration of individuals (Aim 5) and to test whether specific alter characteristics are associated with individual-level social integration (Aim 6).

Within this study, I identify key features of alters binding the personal and associational spaces of an individual social world. I find that (1) similarly aged alters are most influential in bridging personal and associational ties, (2) spouses are integral to individual social integration, (3) strong ties that are long-lasting and frequently activated are highly influential, and (4) social integration is contingent on the context in which ties are formed. These findings sharpen sociological understandings of the importance of relationship characteristics, the strength of weak ties, and the influence of social connections on individual outcomes.

5.4 METHODOLOGICAL LIMITATIONS

Despite the promise of the approach developed in this dissertation, there are a number of important limitations that need to be acknowledged. I will focus on two main types of limitations that inform each other: methodological limitations and data limitations. While this dissertation contributes to literature on social integration, its data structure and measures are only a first step and may be limited in a variety of ways. For example, implicit within these analyses is the assumption that both personal (alter-alter) and associational (alter-association) ties hold the same weight for integration. While the studies identified the complexity of personal and associational ties, illustrating that they can, depending on the context, either supplement integration or differentially integrate PANs, each type of tie holds the same weight. This may not adequately capture the differences in personal and associational ties. Thus, future research should consider additional weighting of ties that can better account for these differences. Additionally, when focusing on the supplemental role of voluntary associations, future studies ought to identify which associational ties are likely to supplement personal ties most effectively, especially for individual outcomes such as mental health, social support, and the like.

While the PAN framework is theoretically grounded, few datasets exist that can be used to validate these measures. Typical ego network studies do not account for other tie types, let alone how alters are directly linked to them. It is important for researchers interested in the relational attributes of individuals to identify ways of incorporating more detailed tie measures within their studies. As a way forward, researchers collecting ego network data with alter-alter ties may consider how other relational ties influence their outcomes of interest. If researchers are eliciting alter-

alter ties, incorporating an additional tie elicitation type may be easily incorporated within their surveys. Because few data sources exist that fit the conditions of a PAN approach, I used the NVAS. While the NVAS is a fruitful data source, it is also dated. Its data, collected in 2006, may not accurately capture the social integration properties of social life today. Other surveys may better capture “groups” and ties beyond voluntary associations. For example, with the rise of the digital age, online groups and online social ties also overlap and influence individual integration. While the NVAS is limited in the types of groups it measures, future studies should apply a PAN approach to other groups that better represent today’s social context.

Additionally, the analyses in the third study (Chapter 4) assume an extreme case of tie loss, where all alter-alter and alter-association ties are dropped. This approach may not directly measure how social ties change, grow, or deteriorate over time. Relationships are complex, and a loss of one tie may not indicate a complete loss of all ties. For example, an ego may drop out of an association but may retain personal ties to alters who were co-members of that organization. To better account for such nuances, future studies should identify other dynamic properties of ego networks that can be applied to PANs.

Another limitation exists as a byproduct of using sampled ego network data. In particular, there are no direct ties linking associations to each other (association-association ties). Within the PAN adjacency matrix, there is an unknown set of ties that could possibly exist. Moreover, there is no way to pair associations together in the ego network contexts; rather, associations are either indirectly tied through shared memberships of alters or indirectly tied though egos being members of multiple organizations. As a way forward, researchers could develop a way to pair public data to specific organizations or use a more isolated context where all necessary information exists (e.g., within a single organization). Alternatively, using a PAN approach, an association-association tie could be assumed if an alter shares a membership to two of the same associations as an ego. While I did not make such an assumption in constructing PANs or calculating the PAN measures, future studies could examine how these assumed ties influence integration. Importantly, however, scholars must think carefully about what an association-association tie means in the context of individual integration.

Next, within the NVAS, the name generator is capped at five discussion partners. There may be additional individuals to whom egos are socially connected and with whom they also share other relational connections (i.e., voluntary association memberships). Having a broader set of possible alter nominations may better capture the spread and connectivity of an individual's immediate social environment. Future research could, for example, explore how changing the number of possible alter nominations affects overlap in other social spaces. Importantly, however, researchers ought to be cognizant of the costs and benefits when expanding the number of nominated alters, particularly using a PAN approach. For example, as the number of alters is increased, the number of questions posed to the respondent also increases, as there are several questions about each alter.

Similarly, the number of voluntary association memberships identified by the respondent is not an exhaustive list of possible associations an individual could be a part of. Additionally, because I sought to develop a baseline data structure and set of measures, I treated voluntary associations as a single membership type, though alters may have multiple memberships to the same types of organizations. In the

NVAS, although a respondent could identify multiple organization types, the link between an alter and an association was only specific to the organization type and not differentiated across the number of voluntary associations of the same type identified by the respondent. Therefore, if future research is interested in the more complex social ties across more voluntary associations and their overlap with personal ties, researchers will have to add alter-association ties that identify each specific organization to which the ego is tied rather than only broader organizational types.

Finally, the re-interviewed sample selection, complex network generators, and subsample selection criteria may have led to selection and measurement errors. First, subgroups may be homogeneous because of commonalities in how individuals were selected for the NVAS. These data properties may explain the lack of variation across demographic subgroups, as found in Chapter 3. Additionally, the more detailed alter-association tie generator within the NVAS could yield additional error in measurement of PANs. To better address some of these limitations, future studies could utilize other modes for collecting such detailed network data and identify whether similar patterns of overlap operate across a different sampling frame.

5.5 FUTURE RESEARCH

There are many ways in which this methodological framework could be extended, among them these four: (1) the framework's substantive implications for social integration, (2) the extension of the framework to other types of social ties, (3) the application of the framework to dynamic ego networks, and (4) the relationship of the framework to other network approaches.

First, this dissertation developed a methodological framework for incorporating more types of ties within ego networks and did not explore how these network measures could be used to predict individual-level outcomes. Extant literature has identified the role of social integration in influencing the health, well-being, and social support of individuals. Future studies could take the PAN framework developed in this dissertation and explore how these network features influence, for example, an individual's access to social support and their mental health; in light of those findings, the studies could then identify ways to mitigate loneliness. While I utilized the PAN measures primarily as dependent variables, future studies could use the PAN measures as independent variables to predict any number of individual-level outcomes, thus contributing to research on social integration.

Second, this dissertation was limited to personal and associational ties of individuals. There are, in reality, many other types of ties that constitute an individual's social environment, including those related to work, school, and family. More directly measuring ties and their overlap for any of these settings would be useful for researchers and practitioners concerned about social integration, social support, and community engagement. Additionally, given today's social context, extending a PAN approach to a broader set of groups may illuminate the ways in which civil society is now constituted by a more diverse set of ties. For instance, future research could identify which digital groups (e.g., Twitter, Facebook, or other online platforms) individuals participate in, whether they overlap with in-person groups, and what this tells us about civil society. The PAN approach developed in this dissertation allows for these overlapping tie sets and may inform how social integration operates in social life today.

Third, social worlds are not fixed, but rather living and evolving environments that shrink, grow, and change over time. A large body of research has used ego networks to dynamically model these changes (Bidart and Degenne 2005; Bidart, Degenne, and Grossetti 2020; Cornwell 2003; McPherson and Rotolo 1996). This is a clear avenue of research where a PAN context could be applied. This methodological framework, for example, could be used to explore the consequences of shocks to a PAN for an individual. Such analyses could empirically test how much influence spousal ties have if, for example, a divorce occurs. Incorporating dynamic network properties within a PAN context would provide more detail around the specific consequences tie loss or tie formation has on individuals, especially across both personal and associational ties.

Finally, there are additional methodological advances that have been created to better capture the relational structure of social life. Multi-level networks, for example, assume many of the same dependencies as a PAN approach. Although many of the methodological innovations better accounting for multiple tie types are within a sociocentric (i.e., full) network context, a PAN approach can be adapted to account for other complex relational features within an ego network context. Future research should identify how similar processes operate across other network approaches, including multi-layer networks, multi-level networks, and bipartite networks.

5.6 IMPLICATIONS

Overall, this dissertation contributes to the sociological theory and methods around social integration and the consequences social connectivity has for individuals (Berkman and Glass 2000; Campbell and Lee 1992; Herrmann-Pillath 2000; Hughes and Gove 1981; Louch 2000; Seeman 1996; Turner and Turner 2013). Although it only extends personal networks to incorporate a single additional tie type, this dissertation identifies important nuances in the way that social ties influence network structure and the connections between personal and associational spaces.

This methodological framework can be extended to other substantive cases with similar structural properties, not limited to personal ties and ties to voluntary associations. For example, egos may share ties to paid associations with their close confidants. Sharing more exclusive ties may integrate egos in ways that differ from ties to voluntary associations. The detailed data structure and measures provide researchers with practical tools for studying multiple types of social ties within an ego network. Prior to this dissertation, developments in social network studies capturing multiple (and overlapping) social ties have been limited, as prior research either fails to combine personal and associational ties directly or is limited to full, sociocentric network data. This dissertation extends current network methods to inform how ego networks are structured in more complex ways, and its measures can be used as a practical tool for identifying how the integrating features of personal networks influence substantive outcomes such as health, well-being, and social support.

The dissertation's methodological tools can be applied to current social problems, such as the COVID-19 pandemic. Given the unexpected and unprecedented change to social life, there has not been a more pressing time to understand how individuals are integrated within a larger social context and the consequences of their social ties. The PAN data structure and corresponding measures provide a potential process for identifying multiple social ties within ego networks. A researcher, for example, could explore how PAN structure is associated with COVID-19 risk or, alternatively, how COVID-19 precautions influence individual well-being.

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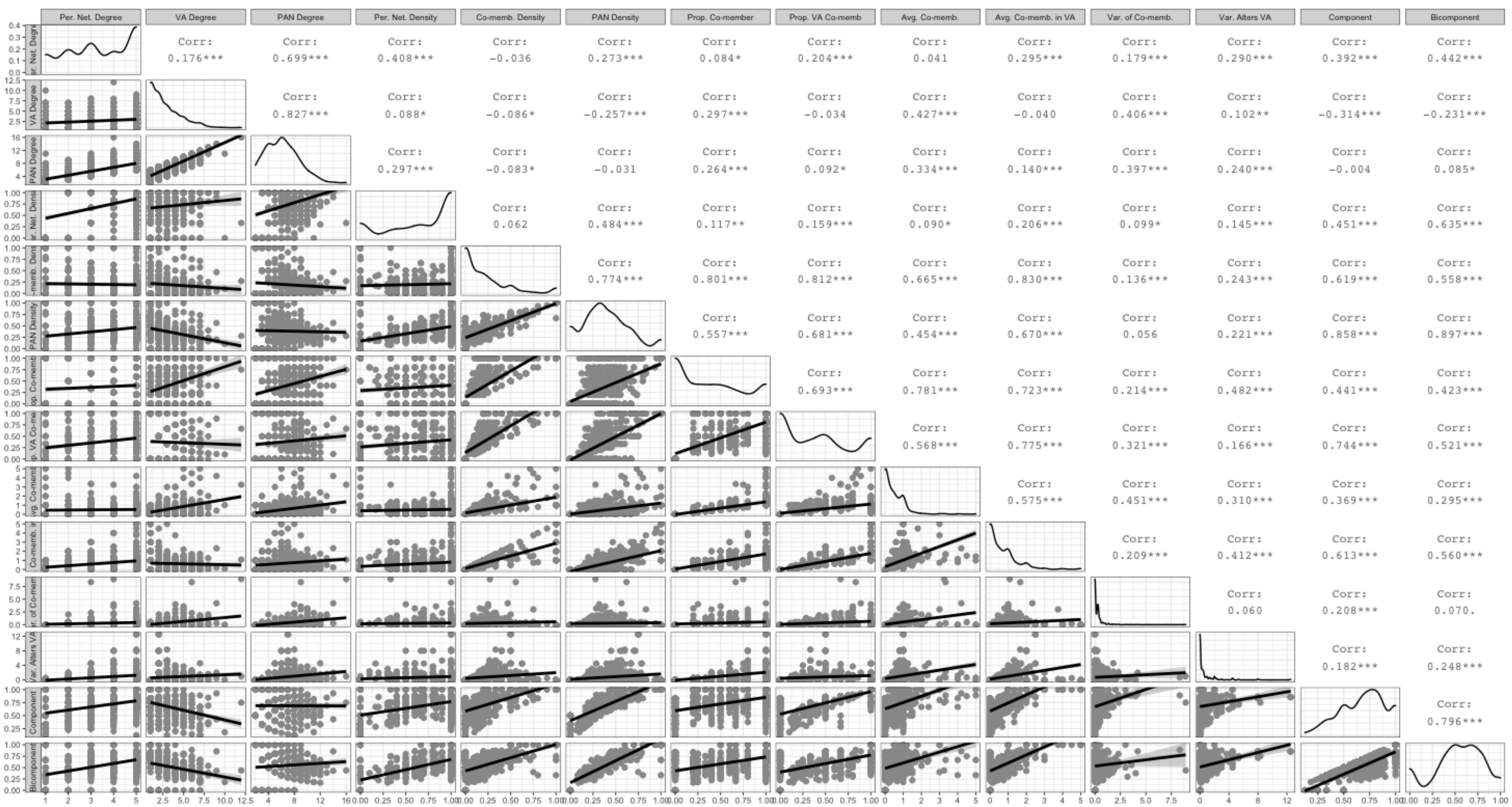
APPENDIX

Appendix 3.A Full Correlation Matrix—All Personal Affiliation Network Measures



Appendix 3.B Group mean differences across all PAN measures by Gender

	Male	Female
Network Size Measures		
Personal Network Degree	3.303	3.487
VA Degree	2.626	2.705
PAN Degree	5.930	6.192
Network Density Measures		
Personal Network Density	.655	.731*
Co-membership Density	.226	.192
PAN Density	.397	.398
Co-membership Specific		
Proportional Composition		
Prop. Co-member	.407	.360
Prop. of VA with Co-members	.380	.385
Magnitude of Co-membership		
Average Co-membership	.517	.515
Average Co-members in VA	.746	.652
Co-membership Concentration		
Concentration of Co-membership	.283	.299
Concentration of Alters in VA	.833	.690
PAN Cohesion		
Fraction in the Largest Component	.684	.706
Fraction in the Largest Bicomponent	.546	.551
N	265	369

*$p < .05$, ** $p < .01$, *** $p < .001$

Appendix 3.C Group mean differences across all PAN measures by Race

	White	Nonwhite
Network Size Measures		
Personal Network Degree	3.529	2.959**
VA Degree	2.612	2.902
PAN Degree	6.141	5.861
Network Density Measures		
Personal Network Density	.735	.560***
Co-membership Density	.208	.200
PAN Density	.413	.341*
Co-membership Specific		
Proportional Composition		
Prop. Co-member	.390	.339
Prop. of VA with Co-members	.392	.350
Magnitude of Co-membership		
Average Co-membership	.520	.500
Average Co-members in VA	.718	.591
Co-membership Concentration		
Concentration of Co-membership	.285	.321
Concentration of Alters in VA	.810	.520
PAN Cohesion		
Fraction in the Largest Component	.711	.643**
Fraction in the Largest Bicomponent	.570	.469**
N	502	132

*$p < .05$, ** $p < .01$, *** $p < .001$

Appendix 3.D Group mean differences across all PAN measures by Education

	< BA	BA	> BA
Network Size Measures			
Personal Network Degree	3.319	3.448	3.666
VA Degree	2.369	2.983	3.210
PAN Degree	5.688	6.430	6.876
Network Density Measures			
Personal Network Density	.656	.754	.756
Co-membership Density	.209	.214	.184
PAN Density	.404	.401	.370
Co-membership Specific			
Proportional Composition			
Prop. Co-member	.352	.413	.421
Prop. of VA with Co-members	.365	.429	.369
Magnitude of Co-membership			
Average Co-membership	.477	.574	.557
Average Co-members in VA	.659	.763	.686
Co-membership Concentration			
Concentration of Co-membership	.232	.329	.441
Concentration of Alters in VA	.691	.637	1.131
PAN Cohesion			
Fraction in the Largest Component	.699	.699	.687
Fraction in the Largest Bicomponent	.547	.546	.560
N	360	169	105

Appendix 3.E Group mean differences across all PAN measures by Religion

	Protestant	Catholic	Oher	None
Network Size Measures				
Personal Network Degree	3.523	3.302	2.960	3.551
VA Degree	2.693	2.826	2.844	2.200
PAN Degree	6.216	6.128	5.803	5.751
Network Density Measures				
Personal Network Density	.722	.701	.627	.672
Co-membership Density	.232	.162	.228	.162
PAN Density	.420	.369	.383	.371
Co-membership Specific				
Proportional Composition				
Prop. Co-member	.429	.338	.360	.274
Prop. of VA with Co-members	.418	.351	.378	.304
Magnitude of Co-membership				
Average Co-membership	.560	.421	.728	.312
Average Co-members in VA	.795	.552	.534	.657
Co-membership Concentration				
Concentration of Co-membership	.324	.279	.235	.248
Concentration of Alters in VA	1.008	.496	.357	.515
PAN Cohesion				
Fraction in the Largest Component	.718	.670	.679	.674
Fraction in the Largest Bicomponent	.578	.520	.487	.537
N	331	138	77	88

Appendix 3.F Pairwise Group Mean Differences between PAN Measures and Education

	<BA-BA	<BA->BA	BA->BA
Network Size Measures	<BA	BA	>BA
Personal Network Degree	-.129	-.347	-2.18
VA Degree	-.614*	-.841*	-.227
PAN Degree	-.742*	-1.188*	-.446
Network Density Measures			
Personal Network Density	-.098*	-.100*	-.002
Co-membership Density	-.005	.025	.030
PAN Density	.003	.034	.031
Co-membership Specific			
Proportional Composition			
Prop. Co-member	-.061	-.069	-.008
Prop. of VA with Co-members	-.064	-.004	-.060
Magnitude of Co-membership			
Average Co-membership	-.097	-.080	.017
Average Co-members in VA	-.104	-.027	.077
Co-membership Concentration			
Concentration of Co-membership	-.097	-.209	-.112
Concentration of Alters in VA	.054	-.440	-.494
PAN Cohesion			
Fraction in the Largest Component	.000	.012	.012
Fraction in the Largest Bicomponent	.001	-.013	-.014

* Significantly different means at $p < .05$

Appendix 3.G Pairwise Group Mean Differences between PAN Measures and Religion

	Protest.-Cath.	Protest.-Other	Protest.-None	Cath.-Other	Cath.-None	Other-None
Network Size Measures						
Personal Network Degree	.221	.563	-.028	.342	-.249	-.591
VA Degree	-.133	-.151	.493	-.018	.626	.644
PAN Degree	.088	.413	.465	.325	.377	.052
Network Density Measures						
Personal Network Density	.021	.095	.050	.074	.029	-.045
Co-membership Density	.070	.004	.070	-.066	.000	.066
PAN Density	.051	.037	.049	-.014	-.002	.012
Co-membership Specific						
Proportional Composition						
Prop. Co-member	.091	.069	.155	-.022	.064	.086
Prop. of VA with Co-members	.067	.040	.114	-.027	.047	.074
Magnitude of Co-membership						
Average Co-membership	.139	-.168	.248	-.307	.109	.416
Average Co-members in VA	.243	.261	.138	.018	-.105	-.123
Co-membership Concentration						
Concentration of Co-membership	.045	.089	.076	.044	.031	-.013
Concentration of Alters in VA	.512	.651	.493	.139	-.019	-.158
PAN Cohesion						
Fraction in the Largest Component	.048	.039	.044	-.009	-.004	.005
Fraction in the Largest Bicomponent	.058	.091	.041	.033	-.017	-.050

* Significantly different means at $p < .05$

Table 3.H Weighted OLS Regression Models Predicting Network Degree Measures

	Personal Network Degree		**VA Degree**		**PAN Degree**	
	M1	M2	M1	M2	M1	M2
Female	.242	.231	.144	.131	.386	.361
Race (non-white)	-.607***	-.485**	.393	.544*	-.214	.058
Education						
BA	.110	-.033	.718***	.541**	.828**	.508*
> BA	.415*	.289	.851***	.693**	1.266***	.982***
Religion						
Catholic	-.263	-.183	.160	.259	-.103	.076
other	-.618*	-.547*	.032	.120	-.586	-.427
none	.021	.200	-.563**	-.341	-.541	-.141
Age	-.001	-.000	.004	.005	.003	.004
Any Co-membership		.953***		1.186***		2.139***
Intercept	3.478***	2.845***	2.048***	1.260***	5.527***	4.105***
N	636	636	636	636	636	636
R^2	.061	.159	.062	.157	.053	.218

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.I Weighted OLS Regression Models Predicting Network Density Measures

	Personal Network Density		Co-membership Density		PAN Density	
	M1	M2	M1	M2	M1	M2
Female	.094**	.092**	-.041	-.045*	-.001	-.004
Race (non-white)	-.177***	-.158***	-.011	.032	-.081*	-.049
Education						
BA	.098*	.076*	.009	-.042	-.005	-.043
> BA	.119**	.099*	-.031	-.076***	-.031	-.065*
Religion						
Catholic	-.034	-.022	-.075**	-.047*	-.060*	-.039
other	-.117	-.106	.001	.026	-.035	-.017
none	-.065	-.037	-.074	-.011	-.056	-.009
Age	-.001	-.000	-.000	.000	-.001	-.001
Any Co-membership		.148***		.340***		.253***
Intercept	.689***	.591***	.268***	.042	.479***	.311***
N	636	636	636	636	636	636
R^2	.075	.110	.024	.393	.028	.250

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 3.J Weighted OLS Regression Predicting Co-membership Specific Measures

	Proportional Composition				**Magnitude of Co-membership**				**Co-membership Concentration**			
	Prop. Co-Member		Prop. of VA with Co-members		Ave. Co-memb.		Ave. Co-members in VA		Concentration of Co-mem. (Alter)		Concentration of Co-mem. (VA)	
	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Female	-.042	-.049*	.004	-.003	-.011	-.020	-.091	-.104	.033	.027	-.109	-.122
Race (non-white)	-.044	.034	-.046	.033	-.014	.092	-.128	.015	.046	.105	-.288	-.140
Education												
BA	.075	-.016	.072	-.021	.117	-.008	.113	-.055	.116	.046	-.006	-.180
> BA	.065	-.016	.008	-.074**	.063	-.048	.027	-.121	.218	.156	.447	.292
Religion												
Catholic	-.101*	-.050*	-.076	-.024	-.145*	-.076	-.268**	-.174**	-.041	-.002	-.539***	-.441**
other	-.076	-.031	-.047	-.001	.156	.218	-.266*	-.183*	-.114	-.080	-.672***	-.586***
none	-.162**	-.048	-.135*	-.019	-.261***	-.105*	-.156	.054	-.083	.005	-.432	-.215
Age	.001	.001	-.001	-.001	.001	.001	.000	.001	.001	.001	.005	.006
Any Co-membership		.610***		.622***		.831***		1.121***		.467***		1.163***
Intercept	.410***	.005	.453***	.040	.499***	-.054	.829***	.085	0.197*	-.113	.823**	.050
N	636	636	636	636	636	636	636	636	636	636	636	636
R^2	.040	.631	.024	.641	.034	.348	.026	.376	.017	.118	.047	.155

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 3.K Weighted Fractional Regression Predicting PAN Cohesion Measures

	Fraction in the Largest Component		Fraction in the Largest Bicomponent	
	M1	M2	M1	M2
Female	.022	.019	.008	.006
Race (non-white)	-.081**	-.051*	-.111**	-.084**
Education				
BA	-.001	-.036	-.003	-.035
> BA	-.005	-.036	.020	-.008
Religion				
Catholic	-.055*	-.036	-.068*	-.050
other	-.040	-.023	-.093*	-.077*
none	-.053	-.009	-.044	-.005
Age	-.001	-.001	-.001	.000
Any Co-membership		.236***		.211***
Intercept	.775***	.619***	.621***	.481***
N	636	636	636	636
R^2	.038	.300	.043	.181

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4.A Weighted Group Mean Comparison between Alter Homophily Measures across Seven PAN Influence (Inf.) Measures

	Same Sex			Same Race			Same Education			Same Religion		
	Yes	No	t-value	Yes	No	t-value	Yes	No	t-value	Yes	No	t-value
Inf. Personal Network Density	47.48	50.77	2.46*	48.86	46.79	-.86	48.10	48.91	.54	48.33	48.96	.42
Inf. Co-membership Density	23.00	32.65	4.73***	25.87	30.54	1.36	26.43	26.37	-.03	25.92	26.91	.64
Inf. PAN Density	38.73	46.75	6.54***	41.32	43.41	.78	40.83	41.92	.94	41.36	41.76	.33
Inf. Prop. Co-member	23.27	32.18	4.43***	26.85	30.76	1.50	26.46	26.37	-.05	25.71	27.16	.96
Inf. Prop. of VA with Co-members	11.09	21.44	4.75***	14.42	17.16	.76	16.21	13.96	-1.12	14.84	14.60	-.14
Inf. Fraction in Largest Component	20.96	27.20	6.38***	22.80	25.96	1.96†	23.11	23.17	.07	22.66	23.69	1.19
Inf. Fraction in Largest Bicomponent	23.20	30.11	4.81***	25.34	27.94	.78	25.45	25.71	.21	25.96	25.26	-.55
N	981	497		1,333	145		498	980		803	675	

Appendix 4.B Weighted Multi-level and Clustered OLS Regression Models, Homophily Characteristics Predicting Alter Influence[1,2]

	Inf. Personal Net. Density[a]	Inf. Co-mem. Density[b]	Inf. PAN Density[a]	Inf. Prop. Co-member[b]	Inf. Prop. VA w/ Co-memb.[b]	Inf. Frac. in Largest Comp.[a]	Inf. Frac. in Largest Bicomp.[a]
Homophily Characteristics							
Same Sex	-4.309***	-9.768***	-7.854***	-9.007***	-10.91***	-6.117***	-7.113***
Same Race	2.953	-2.935	-.171	-3.620	-1.270	-2.356	.023
Same Education	.204	-.397	-.860	-.292	1.805	-.003	-.529
Same Religion	2.189	.608	1.772	.186	1.524	.380	2.676
Abs. Difference Age	-.046	-.568***	-.238***	-.542***	-.497***	-.165***	-.184***
Control Variables							
Sex (female)	2.149	2.747	2.113*	2.694	5.569**	1.500	2.192
Race (non-white)	.571	1.033	1.862	.312	.959	.520	3.433
Education							
BA	-1.438	-.557	-.394	-.842	.450	.443	-.303
HT BA	-1.598	-.645	-.399	-1.127	2.097	.807	-.811
Religion							
Protestant	-2.342	.832	.379	.624	1.728	.482	1.266
Catholic	-2.061	-.715	-.171	-.974	1.362	.162	.277
other	-1.498	-2.439	.586	-2.272	-.225	-.288	3.853
Age	.010	-.053	-.024	-.044	-.064	-.026	-.030
PAN Degree (centered)	-2.357***	-2.729***	-3.661***	-2.700***	-2.607***	-2.429***	-2.599***
Intercept	49.98***	43.31***	49.28***	43.35***	25.84***	31.46***	31.00***
σ^2(ego)	314.1***	–	21.720	–	–	24.94**	70.65*
σ^2(Intercept)	261.3***	–	239.3***	–	–	142.9***	343.7***

[1] Estimates are weighted, and standard errors are adjusted for clustering and stratification.; [2] Analytic sample is comprised of 1,478 alters nested in 393 egos.

[a] Multilevel Generalized Regression Models; [b] Clustered OLS Regression Models

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4.C Multi-level and Clustered OLS Regression Models, Tie Characteristics Predicting Alter Influence[1,2]

	Inf. Personal Net. Density[a]	Inf. Co-mem. Density[b]	Inf. PAN Density[a]	Inf. Prop. Co-member[b]	Inf. Prop. VA w/ Co-memb.[b]	Inf. Frac. in Largest Comp.[a]	Inf. Frac. in Largest Bicomp.[a]
Tie Characteristics							
Tie Type							
Role Relation							
Spouse	7.174***	16.72***	13.62***	14.28***	21.46***	11.68***	12.21***
Other Kin	.867	-13.91***	-2.868*	-14.20***	-8.817***	-1.844*	-2.018
Tie Strength							
Length of Relationship							
5-10 yrs.	6.313**	-.712	2.228	-.244	.128	1.476	1.895
10+ yrs.	6.516***	3.579	4.590**	3.968	6.678*	2.453	3.845*
Interaction Frequency							
Weekly	4.310**	5.674**	4.683***	5.751**	3.210	2.337**	4.427**
Daily	6.150**	11.72***	7.712***	11.63***	8.044**	4.181***	6.643***
Control Variables							
Sex (female)	1.623	2.200	1.311	2.171	4.792**	1.047	1.415
Race (non-white)	-.288	2.780	2.355	2.319	2.185	1.749	3.798
Education	-.905	-.439	-.166	-.712	.829	.441	-.044
BA	-.655	.211	.387	-.255	2.947	1.272	.002
HT BA	-2.694	.988	.353	.621	1.344	-.168	1.874
Religion	-2.836	.142	-.388	-.158	1.514	-.164	.580
Protestant	-1.900	-1.297	.967	-1.206	.368	-.164	4.129
Catholic	-.004	-.071	-.039	-.065	-.105	-.032	-.036
other	-2.097**	-2.531***	-3.454***	-2.540***	-2.305***	-2.273***	-2.332***
Age	40.76***	20.15***	33.03***	20.53***	5.516	18.40***	16.71***
PAN Degree (centered)	331.9***		19.380			24.19**	53.230
Intercept	241.8***		212.9***			127.1***	334.6***
σ^2(ego)	7.174***	16.72***	13.62***	14.28***	21.46***	11.68***	12.21***
σ^2(Intercept)	.867	-13.91***	-2.868*	-14.20***	-8.817***	-1.844*	-2.018

[1] Estimates are weighted, and standard errors are adjusted for clustering and stratification.; [2] Analytic sample is comprised of 1,478 alters nested in 393 egos.
[a] Multilevel Generalized Regression Models; [b] Clustered OLS Regression Models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 4.D Weighted Multi-level and Clustered OLS Regression Models, Co-membership Characteristic (Met at Association) Predicting Alter Influence[1,2]

	Inf. Personal Net. Density[a]	Inf. Co-mem. Density[b]	Inf. PAN Density[a]	Inf. Prop. Co-member[b]	Inf. Prop. VA w/ Co-memb.[b]	Inf. Frac. in Largest Comp.[a]	Inf. Frac. in Largest Bicomp.[a]
Co-membership Characteristic							
Met at Association	.371	9.731***	.863	10.20***	-2.429	-.071	.712
Control Variables							
Sex (female)	1.201	1.280	.550	1.410	2.981	.216	.719
Race (non-white)	-.935	1.430	1.385	1.029	.941	1.153	2.880
Education							
BA	-1.317	.704	.020	.374	1.758	.833	.063
HT BA	-1.477	1.601	.328	1.100	3.573	1.418	-.203
Religion							
Protestant	-.899	1.746	1.467	1.333	2.012	.561	2.946
Catholic	-1.370	.706	.479	.423	1.418	.351	1.303
other	-1.784	-1.567	.366	-1.329	-.806	-.691	3.569
Age	.001	-0.158**	-0.0683*	-0.146*	-0.138*	-0.0579*	-.065
PAN Degree (centered)	-2.395***	-2.787***	-3.737***	-2.757***	-2.683***	-2.494***	-2.657***
Intercept	50.99***	29.85***	43.97***	29.59***	17.84***	25.44***	26.81***
σ^2(ego)	304.1***		24.040			24.57*	72.040
σ^2(Intercept)	269.1***		258.0***			155.0***	358.9***

[1] Estimates are weighted, and standard errors are adjusted for clustering and stratification.; [2] Analytic sample is comprised of 1,478 alters nested in 393 egos.
[a] Multilevel Generalized Regression Models; [b] Clustered OLS Regression Models
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$